DEVELOPMENT AND EXAMINATION OF MOBILE SENSOR SYSTEMS AND SOFTWARE APPLICATIONS FOR USE IN ESTIMATION OF FORAGE DRY MATTER BIOMASS AND CRUDE PROTEIN

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Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
DOCTOR OF PHILOSOPHY
July, 2015

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ACKNOWLEDGEMENTS

The Author expresses sincere appreciation to the following persons for their contribution and accommodation in enabling and supporting these projects such as to allow to come to fruition the successful outcomes which were achieved

Dr. T.J. Butler
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Date of Degree: JULY, 2015

Title of Study: DEVELOPMENT AND EXAMINATION OF MOBILE SENSOR SYSTEMS AND SOFTWARE APPLICATIONS FOR USE IN ESTIMATION OF FORAGE DRY MATTER BIOMASS AND CRUDE PROTEIN

Major Field: SOIL SCIENCE

Abstract: The use of field-based sensors can generate large amounts of data rapidly for phenomic modeling and management decisions; however some challenges may be encountered. AgriLogger software developed to rapidly acquire data for predictive model construction and implementation. AgriLogger features include user controls for data acquisition rate and a single output file for multiple sensors. Temporal and spatial data parsing was achieved from position and time stamps. Non-destructive biomass estimation of vegetation has been performed via remote sensing. This study examined several types of ground-based mobile sensing strategies for forage biomass estimation in alfalfa (Medicago sativa L.), bermudagrass [Cynodon dactylon (L.) Pers.], and wheat (Triticum aestivum L.). Forage quality analysis has historically been performed on physically collected samples through laboratory methods. Developing a sensor system which can collect data and provide estimates for crude protein (CP) in a more timely manner will allow near real time decision making by mangers. To evaluate the feasibility of such a system bermudagrass tall fescue (Festuca arundinacea Schreb.), and wheat were examined. AgriLogger reduced the post-processing time by a factor of 10 and data acquisition time by a factor of 60 as compared to commercially available alternatives which could be used for sensor data acquisition on vegetation. Predictive models were constructed via partial least squares regression and modeled estimates were compared to the physically measured biomass and CP. Differences between methods were minimal (average percent error of 11.2% for difference between predicted values versus machine and quadrat harvested biomass values (1.64 and 4.91 t ha-1, respectively). The predicted CP regressed with those measured in a laboratory using NIRS produced an R^2 of 0.75 for a hyperspectral model. Wheat model prediction of crude protein bore n R^2 of 0.65 and tall fescue R^2=0.83. These data suggest that using mobile sensor-based biomass and CP estimation models could be an effective alternative to the traditional clipping and laboratory methods for rapid, accurate in-field estimation.

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CHAPTER I

EVALUATION OF A SYSTEM FOR HIGH-THROUGHPUT DATA ACQUISITION AND A MODELING APPROACH FOR FIELD RESEARCH AND PLANT BREEDING

I. *Introduction*

Manual sampling techniques such as tissue collection and plant measurement in plant research and breeding programs are time-consuming and labor-intensive. However, remote sensing of vegetation with an effective data acquisition tool, offers a potentially effective alternative to manual sampling. A mobile system which can traverse an entire research trial or large AOI (area of interest) without stopping for recording point data can allow substantial collections of data to be acquired in relatively small amounts of time. One of the challenges encountered when developing such a system is the software application used for data acquisition. The software application must allow for multiple streams of data to be acquired from multiple sensors (hardware), which generally require different communication configurations. The software strategy used to accommodate data inflow from these sensors also presents a challenge as the rate of emission will most likely be different from some or all hardware employed. Furthermore, post-processing of the data for parsing according to AOI can be difficult as spatial and temporal data must be. simultaneously recorded to correspond with sensor outputs.

II. *Review of Literature*

In large part, remote sensing of vegetation has been used to generate point data on a stop-and-go basis. The data collected from sensors would subsequently be stored on media and extracted after the collection event had concluded. This data collection dynamic has been performed using ultrasonic sensors for dry matter (DM) estimation in pastures (Hutchings et al., 1990; Fricke et al., 2011; Fricke and Wachendorf, 2013;), for canopy characterization in orchards (Zaman and Salyani, 2004; Planas et al., 2011), as well as crop production scenarios in wheat (Triticum aestivum L.) (Scotford and Miller, 2004), cotton (Gossypium hirsutum L.) (Sui and Thomasson, 2006), and corn (Zea mays L.) (Freeman et al., 2007). Laser sensors have also been implemented to collect height data for corn (Selbeck et al., 2010), rape (Brassica napus L.), miscellaneous vegetation (Hopkinson et al., 2006), pasture (Ehlert et al., 2008), rye (Secale cereale L.), standing forests (Henning and Radtke, 2006), and wheat (Ehlert et al., 2010; Fumiki and Omasa, 2009). Utilization of sensor arrays or combinations have also adhered to this same data collection strategy in estimating biomass for white clover (Trifolium repens L.), red clover (Trifolium pratense L.), and alfalfa (Medicago sativa L.) with perennial ryegrass (Lolium perenne L.) (Fricke et al., 2013). Similar examinations were made in corn by Freeman (2007) and canopy height in wheat by Scotford and Miller (2004) using Normalized Difference Vegetation Index (NDVI) and ultrasonic sensors. More recently high-throughput phenotyping systems for plant breeding selection have combined a number of sensors into a system for measuring plant traits and response characteristics as well as modeling water utilization (Sanchez et al., 2014).

Despite this ubiquitous point data trend in sensor data collection, some researchers have begun to examine custom software applications which allow real-time streaming of data into databases or output files and include data processing features prior to storage, allowing greater user control over the incoming data streams. Schuman and Zaman (2005) examined a custom software application for ultrasonic orchard tree canopy size measurement which allowed viewing of real-time data inflow and storage of partially processed data into an access database. This real-time data acquisition method has also been employed for high-throughput phenotyping in wheat (Kipp et al., 2014). Despite some occurrence of custom software applications for acquiring high volume sensor data, a deficit remains in the literature on the basic functions needed for effective use in high-throughput systems.

Objective

The objectives of this research were to examine high-throughput data acquisition methods and to develop a versatile and intuitive software platform to effectively perform the following:

1. Compare the functionality of software capable of logging multiple streams of data with unique communication configurations
2. Allow inflow of multiple streams of digital or analog sensor data simultaneously
3. Accommodate multiple unique configurations for incoming data streams
4. Provide user control of incoming data:
5. Acquisition rate
6. Real-time AOI tagging
7. Provide usability from either touch or mouse click from PC or tablet platforms on Windows OS (Microsoft Corp., Redmond, WA)
8. Allow for additional unique data stream configurations
9. Provide a database for retention of multiple data stream configurations
10. Produce granular data output for modeling
11. Produce AOI averaged raw data
12. Produce AOI averaged modeled data
13. Include optional empirical sensor calibrations
14. Include threshold filtering of sensor data for omission of null values

15. Allow implementation of validated models for decision making

16. Display real-time rolling outcome averages for AOI being sampled

III. *Methodology*

Experiments

An alfalfa -bermudagrass [Cynodon dactylon (L.) Pers.] establishment experiment was conducted on the Noble Foundation Red River Research and Demonstration Ranch near Burneyville, OK (33.88^{o} N, 97.28^{o} W; elevation 234 m.). '600RR' alfalfa was inter-seeded into an established 'Midland 99' bermudagrass sward in autumn of 2012 and spring of 2013. Data were collected four times (May, June, August, and October) during the 2013 growing season. Four replications of treatments were arranged in a randomized complete block design with a split-split-plot arrangement. A four replication RCBD bermudagrass/nitrogen fertilizer rate study was adjacently located and harvested concurrently with the alfalfa-bermudagrass mixture experiment. Sensor data was also acquired over two wheat variety trials comprising 560 entries. One trial was initiated at the Noble Foundation Dupy Farm near Gene Autry, OK (34.29^{o} N, 96.99^{o} W; elevation 220 m.), and the other experiment was located at the Noble Foundation Unit 3 Farm in Ardmore, OK (34.17^{o} N, 97.08^{o} W; elevation 268 m.). Seven data collection events were initiated over the two trials and occurred from February to April of 2014.

Mobile Platforms

An electric golf cart was employed as a ground-based mobile platform for moving sensors across the trial areas in the alfalfa-bermudagrass experiment. A custom-fitted mast was attached to the cart to suspend the sensor array over vegetation in front of the cart. A 12 V power source was also added to the cart and served as the power source for all sensors as well as backup power to the PC. A master power switch was utilized to enable termination or initiation of power to all sensors.

A gasoline-powered Spider high-clearance tractor (LeeAgra, Inc., Lubbock, TX) was employed as the mobile platform for the wheat experiments. The factory-equipped spray mast located at the front of the tractor was converted to accommodate the sensor array. All sensors were powered using an additional 12 V power source retrofitted to the tractor specifically for this application. This system was also outfitted with a master power switch to control power to all sensors.

Sensors

Both platforms were equipped with an OmniStar XP GNSS-enabled GPS emitting positional data at 10 Hz to correspond to all sensor readings. This rate of output provided recording of multiple locations within each AOI. In the alfalfa-bermudagrass experiment, vegetation height data was acquired using two time-of-flight laser distance sensors as well as a 120 MHz ultrasonic sensor. The laser sensed on a 2- to 4-mm footprint, which was inversely proportional to vegetation height. The ultrasonic sensor collected readings centered on a 7.5- to 15-cm footprint, which were inversely proportional to vegetation height. The calibration for height sensors was 0-93 cm, such that both were operated within effective detection limits of near 0 mm to 10 m specified by the manufacturer. Laser and ultrasonic data were acquired at rates from 10 to 50 Hz. In the wheat experiments, vegetation height was acquired at 10 Hz using the same laser and ultrasonic sensors but both were calibrated at 0-74 cm. The systems also included an active field radiometer in order to collect reflectance readings and calculation of NDVI. Data were also acquired at rate of 10 Hz from the active radiometer. Approximately 3-5 seconds of data were acquired per AOI with the assumption the subsequent 30+ sensor readings would provide a representative sample of vegetation height and spectral reflectance.

Physical Vegetation Measurements

In the alfalfa-bermudagrass experiment, physical vegetation height measurements were taken using a meter stick and a 0.1-m^2 aluminum rising plate disk meter (NZ Agriworks LTD t/a Jenquip, Feilding, NZ) (Hakl et al., 2012;Interrante et al., 2012). Hand-separated alfalfa and bermudagrass subsamples were dried in a forced draft oven at 50°C for seven days to a constant weight prior to weighing for percent moisture calculation. Plot biomass weights were recorded on a whole plot basis by clipping plots to a 5-cm stubble height with a Cibus forage harvester (Wintersteiger Inc., Salt Lake City, UT) and are reported on a DM basis. Wheat biomass weights were estimated by hand-clipping a 0.16 m2 quadrat to a 2.5-cm stubble height and dried in a forced draft oven at 50°C for five days prior to weighing and were also reported on a DM basis.

Data Acquisition Hardware

All height measurement sensors were hard-wire connected to a data acquisition module (DAQ) for single stream data acquisition. Laser sensors were current loop configured with an operating range of 0 to 5 VDC. The 120 MHz ultrasonic sensor was also configured with an operating range of 0 to 5 VDC. All height sensor data was transferred from the DAQ as digital output to a laptop computer via USB connection. Data from the active radiometer and GPS were output directly to the laptop computer via RS232 serial connection.

Data Acquisition Software

In both experiments, data were acquired and logged to a .txt file real-time using AgriLogger (Fig. 1.1) and WWP (WinWedge Pro©; TAL Technologies Inc., Philadelphia, PA). (Fig. 1.2) software platforms. Both applications required the user to designate the COM port number which corresponded to specific sensors. These software applications were never employed simultaneously for data acquisition although multiple applications of WWP were simultaneously run to capture multiple streams of data simultaneously. Both applications supported unique configurations for interfacing with each data stream. Additionally, elimination of superfluous data fields with each record from some devices such as hardware identifiers, etc. was possible with both AgriLogger and WWP.

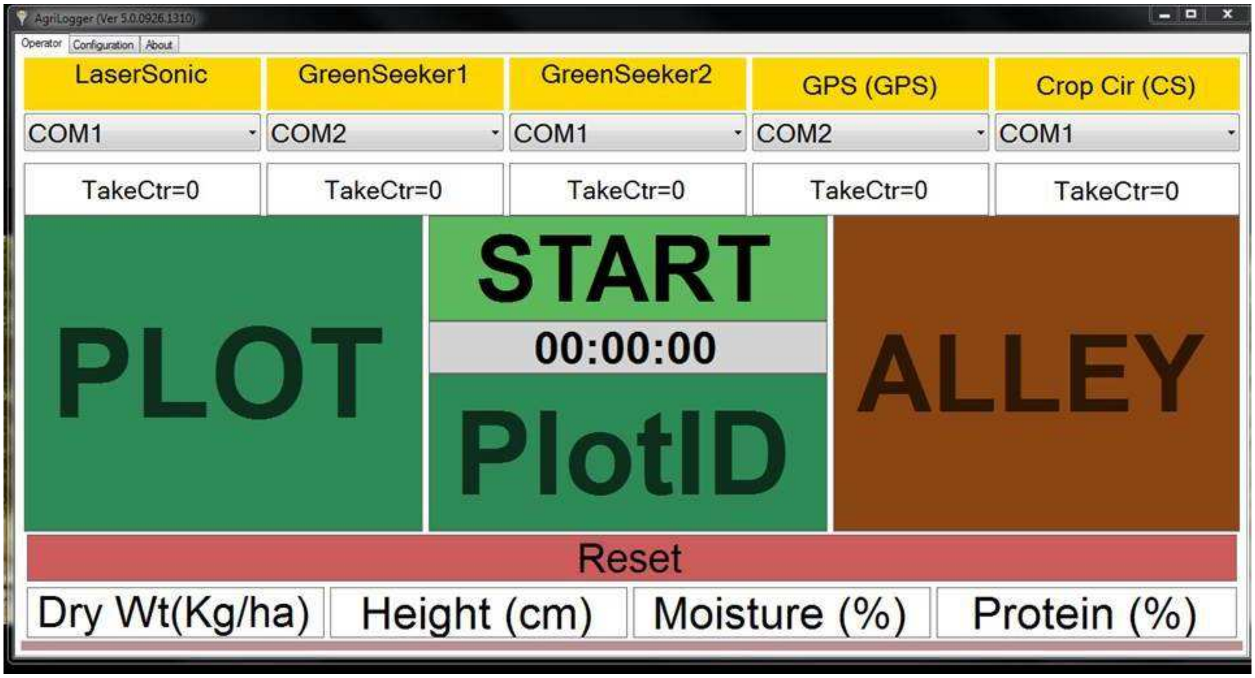

Figure. 1.1. User interface of AgriLogger, an original software application produced by the Samuel Roberts Noble Foundation in 2014. It is designed to be operated from a touch screen device for acquiring serial or digital data from multiple output sources simultaneously in use as a data collection tool for high-throughput data scenarios. This user interface includes areas of interest tagging controls, sensor stream inputs readouts, and model calculation outputs from incoming serial data.

Area of Interest (AOI) Delineation

The power cycling switch was used for plot delineation when acquiring data with WWP. At no point were output data streams interrupted, but as the power was cycled on, sensors would emit data (null readings were acquired when power was cycled off). Intra-AOI areas were delineated by null values in the logged data and AOIs by subsequent recorded sensor outputs. Conversely, AgriLogger enabled the user to insert identifiers real-time as the data were acquired via a mouse click or touch screen button in order to delineate AOIs from intra-AOI areas. When using AgriLogger, intra-AOI identifiers were assigned during the time spent crossing the intra-AOI areas and until all sensors were oriented above the successive AOI. Positional data was acquired simultaneously with spectral and proximal data.

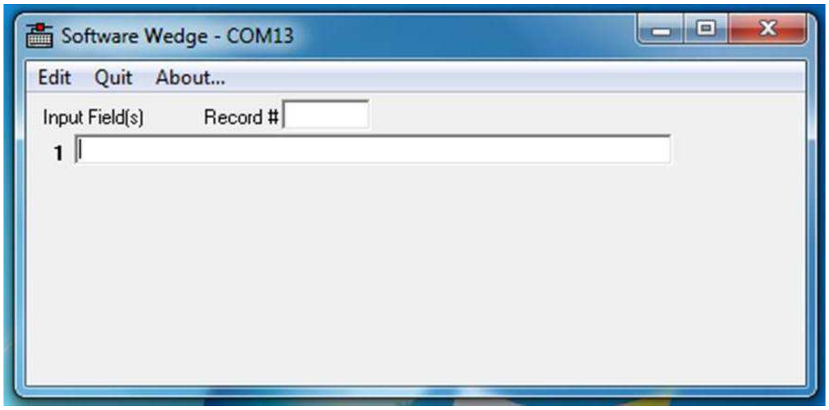

Figure. 1.2. User interface for WinWedge Pro©, a commercially available software application designed to be operated from a pc platform for acquiring serial or digital data from a single output source.

Data Acquisition Rates and Strategies

WinWedge Pro© accommodated capture and logging of serial data. Only one stream of data could be logged for one instance of the running program. As was previously mentioned, this necessitated multiple instances of the application to be run simultaneously to capture and log data from multiple instruments. This also resulted in the production of multiple .txt log files, one for each stream of data. Data contained within each file was logged at the rate dictated by the emitting device which resulted in variable rates across the multiple log files.

AgriLogger allowed a number of incoming data streams, which was only limited by the processing capabilities of the hardware upon which it was installed. This feature was created such that all data streams could be output to a single temporally-spliced log file. AgriLogger tools were designed to employ user controls for data acquisition rate as well as active data tagging for AOI identification and output a .txt file with a number of observations retained for each AOI. A second tool designed to output an additional .txt file containing only parameter averages for each AOI was also employed. These tools enabled the implementation of hard-coded modeling outcome calculations to be output on an AOI basis. An addition feature displayed rolling averages of model outcomes for each sensed AOI on-screen as data were acquired. In order for the this option to output useful information, hardware appropriate models were required. All streams of acquired data were sampled according to the Windows clock utility as opposed to “captured in totality” to allow the .txt log to contain one observation per stream of incoming data at the user dictated rate.

Additional options provided in AgriLogger were height sensor calibration and threshold establishment. These features were installed so that filtering for invalid data (such as results from signal loss) could be performed automatically and not be included in output files. The configuration

Figure.1.3. Configuration tab for AgriLogger allowing user access to sensor communication and data retention protocols as well as sampling rate, data storage location, threshold/calibration entry, and species specific model output selection.

tab allowed access to sampling interval, threshold entry, and protocol configuration as well as file destination for logged data (Fig. 1.3).

Data Transformation

Post-processing data transformation was performed only on laser readings, which were output as inversely proportional to vegetation height (i.e. directly proportional to distance from sensor). Laser readings were subtracted from the maximum output value which signified bare ground surface. This adjusted the data to a directly varying scale and agreed with the relationships between change in height/biomass and sensor output from the ultrasonic and spectral sensors. This transformation calculation was included in the averaging feature for the General utility in AgriLogger.

Data Analysis-All Experiments

Correlation of sensor readings to physically measured vegetation parameters were examined using SAS PROC CORR (Brownell et al., 2012; SAS, 2012; Golodets et al., 2013; Pilliod and Arkle, 2013). These correlations were initially examined to evaluate appropriate variables for modeling analysis inclusion. Models for vegetation parameter estimates were produced using partial least squares (PLS) regression via SAS PROC PLS with CVTEST and NOINT options such that the simplest models would be chosen (SAS, 2012; Chen and Zhu, 2013; Luo et al., 2014; Wuerschum et al., 2014). The cross-validation and model training aspects of PROC PLS allowed it to be used effectively for optimization of estimation model accuracy. To further evaluate suitability of data included in estimation models, Variable Importance Plot (VIP) scores and Centered Scaled Parameter Estimates (CSPE) (Mehmood etal, 2012) were examined.

This strategy was adopted in order to achieve an acceptable balance in estimate accuracy and model/sensor system complexity by excluding less contributive variables from the system. Species-specific and general models were constructed from two-thirds of the total data collected, with the remaining one-third employed as validation data. Predicted versus measured height and biomass parameters from the validation data were regressed using SAS PROC REG (SAS, 2012). Accuracy of estimates was examined as a function of the mean from the sample percent difference between estimates and measured values (Eq. 1.1). Competing indications of model performance were addressed using an Error, Consistency, and Mean Agreement (ECMA) score. The score equally weighted the standard deviation of percent error, mean of percent error, R2 of estimate to measured, as well as the actual difference in mean of estimate as compared to measured values (Eq. 1.2). This score was also calculated for destructively measured biomass from the bermudagrass-nitrogen study. From paired bermudagrass plots, it was possible to calculate repeatability of the destructively harvested method as the plots were in a side-by-side orientation such that an assumption of relative homogeneity could be made. It was necessary to make this comparison in order to create a standard by which the estimation models could be ranked.

$$\text{Mean Percent Error} = \text{Mean} \sum_{n}^{1} \frac{|\text{Estimate} - \text{Measured}|}{\text{Measured Dry Mass}} \qquad \text{(Equation 1.1)}$$

$$\text{ECMA} = \frac{\left(\frac{\text{Coefficient of determination for estimate by measured}}{|\text{estimate mean} - \text{measured mean}|}\right)}{\text{mean percent error} * \text{standard deviation of percent error}} \qquad \text{(Equation 1.2)}$$

IV. *Findings*

WinWedge Pro© Post-Processing

A custom post-processing application was developed in order to streamline handling of data produced using WWP. The primary function of the application was to compress data to a desired rate (i.e. 5 Hz, 10 Hz, etc.) via averaging. This also enabled balancing the number of sensor readings across the sensors and resulted in a more manageable volume of data for AOI-based data parsing. The aforementioned time stamp was employed as the mechanism by which the averaging could be performed. An output file was subsequently created containing the compressed and averaged data at the temporal interval specified by the user. This file could then be manually edited for delineation of AOIs. The AOIs were parsed based on the occurrence of null values as delimiters. It was observed that a sub-second time interval of power ramp-up and ramp-down could be identified in data logged using WWP in conjunction with the master power switch. It was subsequently necessary to identify this area at the beginning and end of each AOI in the logged data and remove it so as to avoid inclusion of erroneous data in AOI averages. Upon combining, filtering, and averaging the data, it was possible to combine the sensor data with physically-measured parameter data for statistical modeling.

AgriLogger Post-Processing

Manual editing of data for removal of non-AOI acquired sensor readings was also necessary when using AgriLogger. The active user control tagging mechanism enabled this to be done efficiently as a non-AOI identifier "A" representing the alley between plots was inserted on each line of data between each identified AOI. The data could then be quickly filtered to eliminate all superfluous information. The sampling logic utilized in AgriLogger also provided that only the user specified rate of data acquisition was retained in the output log file such that no post-process balancing of data was necessary. For output generated by the General utility, user selected model outcomes or parameter averages were retained but no inter-AOI data was included on the output log file.

Data Analysis Efficiency

The projects upon which this software development and evaluation occurred were designed to accommodate collection of data for modeling vegetative parameters. In order to develop the models necessary for parameter estimation, combining physically-measured and sensor-generated data was necessary. When employing WWP as the sensor data collection mechanism, this process was more time-consuming than AgriLogger due to the need to compress and edit the data. The efficiency of AgriLogger was largely a result of the ability to quickly parse AOIs and the accompanying sensor data without the need for compression and normalization of the number of records per each AOI. Averages could then easily be calculated for each AOI using SAS PROC MEANS (SAS, 2012) for model construction. This also created an opportunity to quickly assimilate the averaged data into GIS software such that spatial separation of averaged values could be observed as a quality control measure (Fig. 1.4). This process allowed for the recognition of an apparent spatial offset due to the serpentine pattern by which the AOIs were sampled.

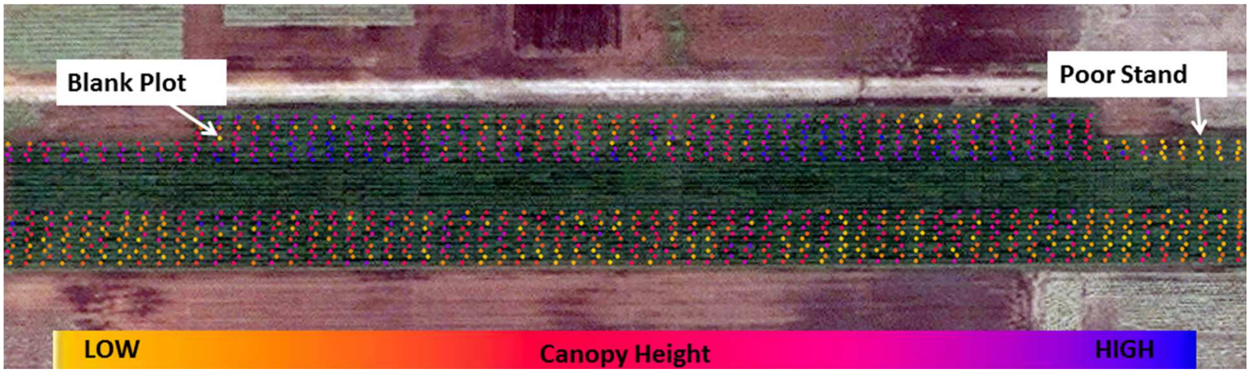

Figure.1.4. Sensed height for wheat experiment used for spatial quality control of offset and ground truthing of sensed data. All data was collected using Agrilogger in combination with a mobile sensor array via a high clearance tractor.

Both software applications were capable of logging data which populated models in much the same manner. This is evident in the Minimum Root Mean Press (MRP) of 0.75 produced from the PLS model when using WWP as compared to that of the AgriLogger data (0.78) (Table 1.1).

This can also be observed by the similarity in the explanation of variation for the dependent variable (VDV) (Biomass) for AgriLogger versus WWP (43 and 48%, respectively). Both sets of data were collected on the initial harvest of the experiment but on different years such that an expectation of similarity is appropriate. From the summary statistics, it can be surmised that the forage production values associated with sensor readings are similar but some variation in distribution and range is present (Table 1.1, Fig. 1.5 and 1.6). Despite some differences in data range and distribution, similar modeling outcomes (VDV, MRP) illustrate that both software applications were effectively implemented for data acquisition. It must be noted that although modeling outcomes were not different when using one application versus the other, the amount of post-processing and data editing associated with the use of WWP was less efficient.

Table 1.1 Summary statistics and model statistics for alfalfa and bermudagrass sensor data modeled using AgriLogger and WinWedge Pro©. Data were modeled using PROC PLS (SAS, 2012) with default permutations and a twenty block folded validation set, and additional summary statistics were generated using PROC MEANS (SAS, 2012).

Model statistics	WinWedge Pro©	AgriLogger	SAS procedure
Number of observations	378	378	PROC MEANS
Minimum	882	230	PROC MEANS
Maximum	7175	11852	PROC MEANS
Mean	3921	3372	PROC MEANS
Standard deviation	1321	2013	PROC MEANS
Extracted factors	2	1	PROC PLS
Minimum Root Mean Press	0.75	0.78	PROC PLS
Explanation of variation in dependent variable	48%	43%	PROC PLS
Inner Regression Coefficients	47%	41%	PROC PLS
	Model effects (%)		
Laser	87	82	PROC PLS
120 Mhz ultrasonic	89	81	PROC PLS
Normalized Difference Vegetation Index (NDVI)	42	87	PROC PLS
	Model weights (%)		
Laser	69	59	PROC PLS
120 Mhz ultrasonic	67	48	PROC PLS
NDVI	31	-66	PROC PLS

Software Performance

Initially, WWP was implemented as the software package for data acquisition. It was quickly recognized that for the most efficient system performance, additional user utilities were necessary. Three aspects which were initially identified as necessary for such a system to function properly were: i). unique configurations for each piece of hardware acquiring and transmitting data, ii). real-time AOI data identification capabilities, and iii). single output file containing all parameters at a standard rate of acquisition. AgriLogger was successfully developed to provide these utilities while WWP only provided the first aspect mentioned above.

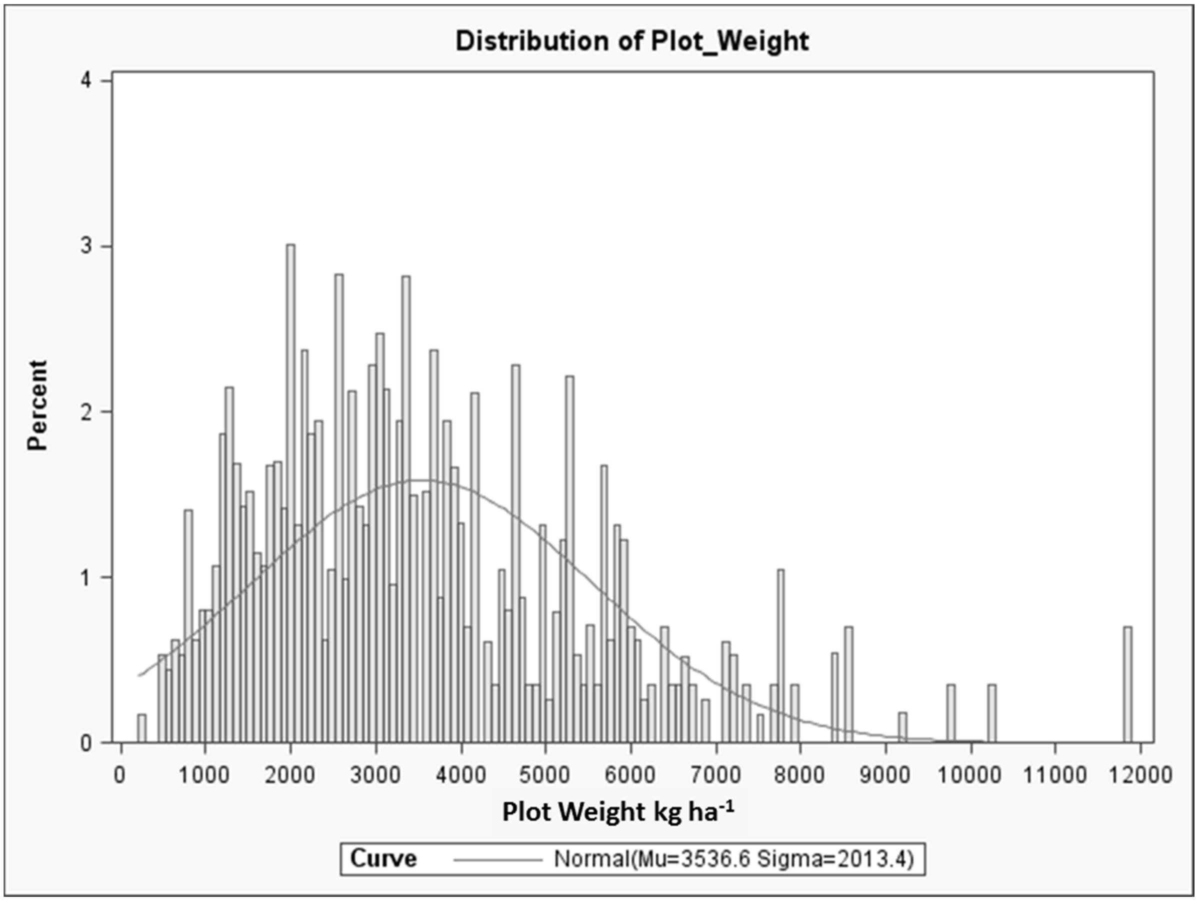

Figure. 1.5. Histogram of forage weights (kg ha $^{-1}$) for alfalfa bermudagrass plots with sensor data collected using AgriLogger and a sensor array from a mobile platform.

The ability of the user to define unique configurations for each piece of data transmitting hardware was necessary due to the fact that interfacing protocols are typically different and may need to be adjusted. In addition, the assimilation of new hardware into the system for additional measurements would likely occur and require a software application with flexible configuration options. It was also observed that devices would transmit undesired data fields such as hardware identifiers with each record. Unique configurations to minimize and/or eliminate the insertion of these data fields were also

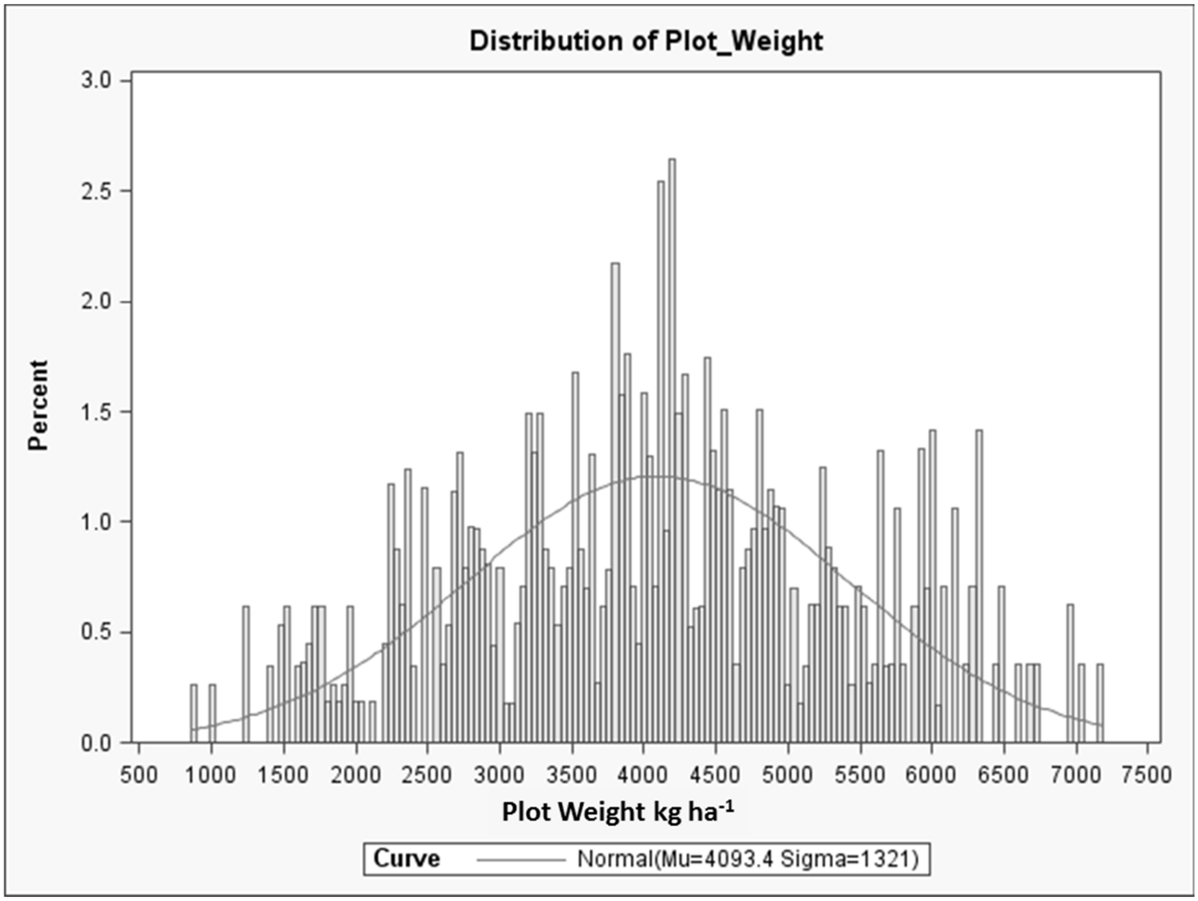

Fig. 1.6. Histogram of forage weights (kg ha $^{-1}$) for alfalfa bermudagrass experiment plots with sensor data collected using WinWedge Pro© and a sensor array from a mobile platform.

necessary in order to reduce recording of unwanted data. Conversely, insertion of a time/date data field for each record was desired in order to merge or parse the data. This insertion required complex configurations in WWP, but was included as a default output field for data acquired using

AgriLogger.

On-the-go identification of AOIs was examined because power cycling in combination with WWP provided a parsing utility which required extensive manual post-processing and the use of additional software. Inserting incremental AOI identifiers satisfied the need for a more efficient mechanism to sort output files and eliminate undesired data in a much more time-effective manner. Acceptable functionality of this feature was observed when applied as an AOI averaging strategy. This utility was not available with WWP and diminished the prospects for continued use of this software for some such high through-put systems.

Possible processing hardware platforms were also a point of examination as the desired end software product would be required to operate on touch screen devices as well as laptop computers. Later in the software development process, it also became necessary to examine hardware platform performance capabilities as a page fault rate spike was initiated due to the magnitude of incoming data. This presented a substantial hindrance in acquiring data at rates in excess of 20 Hz for those devices which transmitted data strings that contained more than five data fields when using WWP (i.e. Active Spectrometer, GPS). Some alleviation of this was achieved at the application level by eliminating the display of the actual incoming data and replacing it with a counter such that an indication of incoming data could still be visually evaluated. It must be noted that even with the inclusion of this "fix," some hardware platforms may not have the processing capabilities to effectively acquire data at rates in excess of 10Hz from multiple sources.

Sensor Calibration and Threshold Establishment

During field use, it is likely that some degradation of static physical sensor orientations may occur. This is less of a consideration for spectral sensors than for proximal sensors as a small change in relative height does not greatly affect spectral reflectance but can deleteriously influence the precision of height measurement instrumentation. In an effort to ensure minimal influence from this type of error, a calibration and filtering feature was included for AgriLogger. This feature was built in as a pop-up block which allowed the option of setting the bare ground threshold reading for the laser and ultrasonic sensors. This threshold was then implemented in the data transformation of the laser data and used as a filter for eliminating invalid data. The scales of measure for both the laser and ultrasonic sensors were linear with static units and allowed effective utilization of this feature in the event the sensor array was re-oriented upward or downward in height. The most recent threshold entry was always retained and used for calculations until the calibration point for minimum height was reset.

V. *Conclusion*

When compared to WWP, AgriLogger provided utilities which allowed for efficient data acquisition from multiple output sources with important user control capabilities for data delineation. Although WWP also allowed for the same type of data to be acquired, inefficiencies in post-processing from AOI delineation and some hardware processing limitations reduced usability in this high-throughput system. Additionally, the single combined output data product resulting from the use of AgriLogger optimized the ability to acquire and evaluate data by reducing time needed to sort and edit files post-processing. The single output file from both the Research and General interfaces also provided an effective mechanism by which the sensor or modeled data could be spatially analyzed using GIS software.

Limitations when using AgriLogger may be encountered when a large number of incoming data streams are acquired, however this maximum has not been observed and will likely be dictated by computing hardware. In order to address real-time spatial parsing of data, an additional utility is currently in development so that a pre-generated AOI spatially reference polygon file could be implemented. This will allow AOI identifiers to be assigned automatically as data is acquired. This feature would only be useful for AOIs with historical spatial data or AOIs for which spatial data was acquired prior to sensing. Future advancements in development of successive AgriLogger versions will need to address repeatable or automatic COM port assignment as this must be verified or designated at the initiation of each use in the current version. The ability to introduce additional models at the user level, which incorporate other types of sensors, will also need to be addressed.

AgriLogger is currently in Beta testing status for application in a variety of venues as a data acquisition tool. Additionally, a remote uplink and data receptacle utilities are currently undergoing testing. This will allow for acquisition, upload and spatial parsing real-time from the field. The intended purposing of the software is for basic research data collection such that modeling of vegetation parameters may be performed for plant breeding selection and agronomic management evaluations. This application could ultimately be employed in livestock or crop production scenarios for high-speed data acquisition and may ultimately enable real-time management decisions.

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CHAPTER II

ESTIMATION OF BIOMASS AND CANOPY HEIGHT IN BERMUDAGRASS, ALFALFA, AND WHEAT USING ULTRASONIC, LASER, AND SPECTRAL SENSORS

I. Introduction

An effective method for in-field estimation of biomass on a dry matter (DM) basis must produce accuracy comparable to the accepted measurement standard (i.e., destructive removal). Non-destructive methods for estimating dry biomass have been developed using plant or canopy measurements (Tucker, 1980; Fricke, 2013). In large part, vegetative mass is considered a function of canopy or plant height (Lati et al.,2013; Machado et al.,2002). For these methods, canopy or plant height is recorded and an empirical relationship between height and DM is developed. Devices such as the rising plate meter, capacitance meter, and meter stick are examples of devices used for physical measurements of vegetation height and biomass estimation (Tucker, 1980; Sanderson et al.,2001; Fehmi et al., 2009; Doughtry.et al, 2013) The limitations associated with these techniques are labor and time intensiveness. Additionally, variation due to vegetation growth characteristics and spatial variability can be difficult to accurately represent by physical sample collection which limits the ability to develop a robust estimation model.

II. Review Of Literature

Alternatively, remote sensing strategies (ultrasonic, laser, and sensor combinations) may overcome some of the limitations encountered with physical measurement strategies. A greater number of measurements can be taken in a considerably reduced amount of time and thus a 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. Ultrasonic proximity sensors employ intensity differential reflectance of sound waves to approximate distances. Ultrasonic sensors have been utilized for measuring height and estimating DM in pastures (Fricke, 2013; Fricke et al.,2011; Hutchings et al.,1990), canopy characterization in orchards (Planas de Marti et al., 2011; Zaman et al.,2004), as well as in wheat (Scotford and Miller, 2004), cotton (Sui and Thomason, 2006), and maize (Aziz et al., 2006). Laser proximity sensors employ time-differential reflectance of light to approximate distances. Laser sensors have been effectively used for height measurements in wheat (Ehlert et al., 2010; Fumiki and Omasa, 2009), maize (Selbeck et al.,2010), rape, rye, pasture (Ehlert et al., 2008), standing forests (Henning and Radtke,2006) and miscellaneous vegetation (Hopkinson et al.,2006). The combination of ultrasonic and active spectral reflectance have been used to estimate biomass in white clover, red clover, alfalfa, and perennial ryegrass, with R2 ranging from 0.90 for estimating alfalfa-perennial ryegrass mixtures to 0.99 for estimation of biomass for monoculture alfalfa (Fricke and Wachendorf, 2013). Combining ultrasonic and Normalized Difference Vegetation Index (NDVI) measurements to estimate canopy height in wheat resulted in standard errors between 4.6 and 7.2 cm (Scotford and Miller, 2004). Similar results were found in maize using NDVI and ultrasonic sensors where an R2 = 0.62 was reported for forage mass (Freeman et al.,2007).

Spectral strategies seek to base biomass estimates on reflectance or absorption intensities of wavelengths from vegetation and/or soil (Fricke and Wachendorf, 2013; Erdle et al.,2011; Hong et al.,2007; Jones et al.,2007). These spectral strategies can be effective at low LAI (Leaf Area Index) and biomass, but can become less accurate as the canopy closes when a point of reflectance saturation may occur (Gnyp et al.,2014; Erdle et al.,2011). Some direct contribution to reflectance saturation can be attributed to increase in vegetation height, but relationships between biomass and NDVI vary logarithmically, signifying an interaction of canopy closure and height (Freeman et al.,2007; Gamon et al.,1995). Normalized difference vegetation index has been employed in biomass estimation for a number of crop species. Freeman (2007) employed an active spectral sensor for calculating NDVI (Greenseeker) and recorded a positive relationship with R2 = 0.52 for forage DM yield in maize. Erdle (2011) reported R2 values of up to 0.91 and 0.84 for nitrogen content and biomass, respectively, when using active spectral sensors for NDVI measurement in wheat. Additionally, Gnyp (2014) observed R2 of up to 0.69 for above-ground biomass in rice when regressed with NDVI alone, as well as a 21-35% increase in explanation of above-ground biomass in rice when using a six-band spectral model as compared to NDVI alone.

Objectives

There is limited published research on the combined use of ultrasonic, spectral, and laser sensors and their subsequent estimation models to measure forage height and DM. Therefore, the objective of this research was to evaluate the relationship between dry biomass measured via destructive removal and dry biomass estimated from a combination of sensor-measured canopy height and spectral reflectance. The evaluation was achieved by collecting both physically-measured and sensor-measured plant canopy heights as well as active and passive spectral reflectance readings via a mobile platform for vegetation at the canopy level. The intended deliverable from this research was a system containing a collection of sensors and software which would enable efficient and accurate acquisition of data by which estimation of dry biomass could be achieved.

III. Methodology

Alfalfa Bermudagrass Experiment : Site, Design, and Management

A ‘600RR’ alfalfa-‘Midland 99’ bermudagrass mixture trial was conducted at the Noble Foundation Red River Research and Demonstration Farm near Burneyville, OK (33.88º N, 97.28º 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 value of 64 g P kg-1, 52 g K kg-1 (amended with 0.1785 t ha-1 0-0-60), B of 0.017 g kg-1 (amended with 0.00745 t kg-1), and pH of 6.3. A Hege 1000 cone planter no-till drill (Hege Equipment Inc., Colwich, KS) was used for inter-seeding alfalfa into an established bermudagrass sward in fall 2012 and spring 2013. Data was collected the following spring and summer after establishment. Treatments were arranged in eight replications of a randomized complete block design (RCBD) with a split-split-plot arrangement. Main plots consisted of three alfalfa planting dates (September, November, and February), subplots consisted of three alfalfa seedbed preparations (mow/hay-off, mow/hay-off plus glyphosate, and tillage), and sub-subplots (1.5 m x 6 m) consisted of seven fungicide and insecticide alfalfa seed treatments. An adjacent experiment with eight replicates of 1.5 m x 6 m bermudagrass only plots treated with seven levels of N fertilizer ranging from 0 to 0.224 t N ha-1 yr-1 was established and harvested concurrently with the alfalfa-bermudagrass mixture experiment.

Physical Measurements: Alfalfa-Bermuda Experiment

Data were collected from all plots four times in 2013 when alfalfa reached 10% bloom. Vegetation height measurements were taken using a meter stick and a 0.1-m2 aluminum rising plate meter (NZ Agriworks LTD t/a Jenquip, Feilding, NZ) (Interrante et al.,2012; Hakl et al.,2021). Species composition was estimated both visually and as hand-separated dry weights from harvested quadrats for the alfalfa and bermudagrass mixtures only (Laliberte et al.,2010). Visual composition was estimated and averaged across two observers (Kercher et al.,2003). Hand-separated alfalfa and bermudagrass subsamples were dried in a forced draft oven at 50°C for five days to a constant weight prior to weighing. Plot biomass weights were recorded on a whole plot basis by clipping plots to a 5-cm stubble height with a Cibus forage harvester (Wintersteiger Inc., Salt Lake City, UT) and are reported on a DM basis.

Sensor Height, Spectral, and Spatial Measurements: Alfalfa-Bermuda Experiment

A ground-based mobile platform was utilized for moving sensors across the trial areas using an electric golf cart (the golf cart was selected due to minimal suspension, Fig. 2.1) fitted with drop spindles and oversized tires spaced at 1 m, to minimize contact with the biomass contained within the plot area (1.5 m x 6 m). The cart was custom-fitted with a mast extending from the front upon which all sensors were attached. A single deep cycle 12 VDC marine battery was added to the cart and served as the power source for all sensors. Power and/or accessory power to all sensors was routed through a system power cycle switch by which all active data acquisition could be initiated or terminated simultaneously. Additionally, a GPS with OmniStar XP GNSS positioning (repeatability <10 cm, 95% CEP) was implemented to acquire position data for all sensor readings. The GPS was configured to output spatial data at a rate of 10 Hz such that multiple locations could be recorded within each plot. Height was measured using a single beam 660 nm time of flight laser distance sensor ("Laser"). The sensor was calibrated (calibration was performed prior to first use and verified by measurement at subsequent data collection events) to bare ground surface (0 cm) and 93 cm above ground surface as minimum and maximum heights, respectively. The laser readings were inversely related to height. The laser sensor used in this experiment differs from LIDAR laser systems which are typically aerial-based or ground-based static as opposed to mobile. Additionally, LIDAR laser systems typically scan a large area, utilize a large number of reflectance beams at numerous wavelengths, and they produce a "point cloud" (Selbeck et al.,2010; Ehlert et al.,2008). The laser distance sensor used in these experiments emitted only one beam at one wavelength to produce a one dimensional pattern of measurements and did not have the multidimensional dynamics of a LIDAR point cloud. The laser readings characterize the height of the vegetation for a 2- to 4-mm diameter footprint which was inversely proportional to vegetation height. Two ultrasonic sensors, operating at different frequencies, were examined to observe appropriateness for use on plant material.

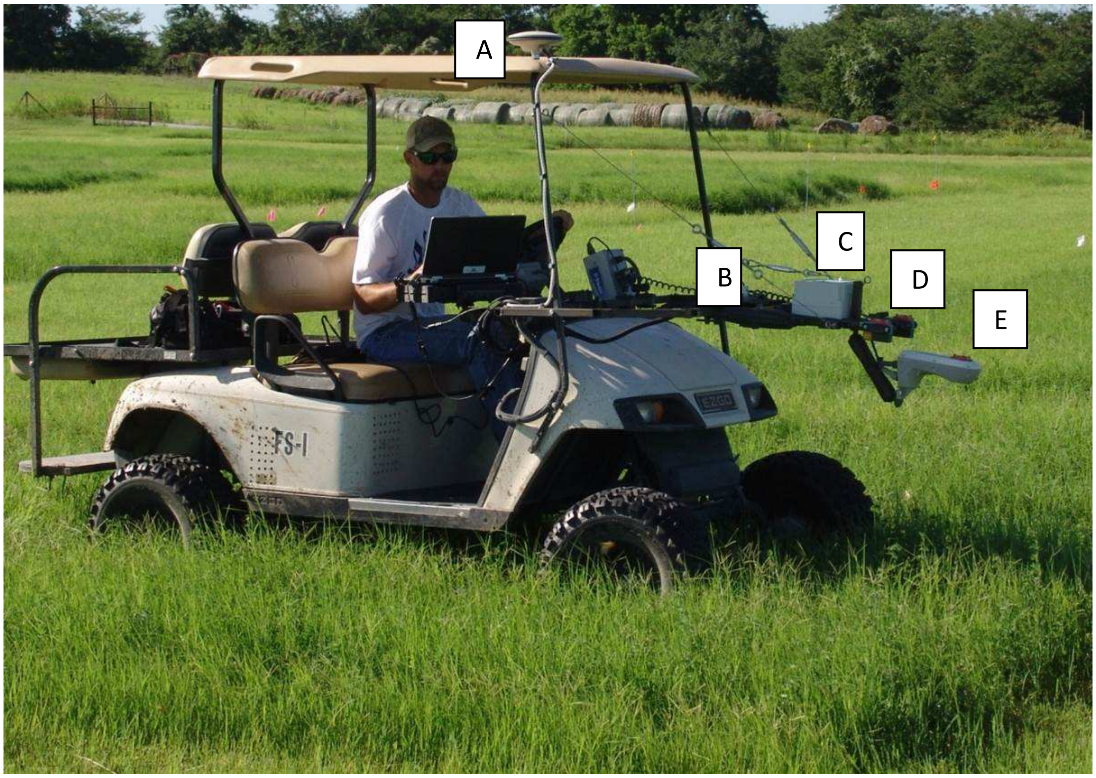

Figure 2.1 Electric golf cart used for transport of sensors across alfalfa-bermudagrass experiment shown with A. GPS, B. Ultrsonic Sensor, C. CropScan radiometer, D.Laser Sesnors, and E. Greenseeker.

Sensor readings were directly proportional height. Readings from the ultrasonic sensors characterized canopy height in a 7.5- to 15-cm conical footprint, which were also inversely proportional to vegetation height. As the calibration for height sensors was 0-93 cm, all were operated within effective detection limits of near 0 m to 10 m specified by the manufacturer. All height data were acquired at the default sensor output rate (50 Hz-150 Hz) and configured to collect data centered on a 0.12 m2 area.

A Greenseeker® (Trimble, Sunnyvale, CA) was employed to collect NDVI with a maximum conical footprint of 0.1 m2 which varied inversely with forage height. Data were acquired at rate of 20 Hz from the Greenseeker® radiometer for each plot. Additionally, a CROPSCAN (CROPSCAN, Inc., Rochester, MN) with a conical footprint having diameter equal to on half of height to target was also used and acquired reflectance measurements at 450, 520, 530, 570, 590, 650, 690, 710, 780, and 900 nm (8.2-13 nm band width). Sampling using the CROPSCAN was limited to two readings per plot in an east/west travel pattern as sampling time was approximately two to three seconds per acquisition. There were fewer CROPSCAN than Greenseeker® readings (two vs. 90 per plot, respectively) since each CROPSCAN acquisition event required a keystroke on the laptop computer compared to an automated acquisition from the Greenseeker® sensor. Prior to data acquisition for the alfalfa and bermudagrass experiment the orientation of the two instruments were adjusted such that no reflectance from the Greenseeker® radiometer influenced readings from the CROPSCAN.

Transport and Temporal Logistics: Alfalfa-Bermuda Experiment

Each plot was driven across at 3.2- 4.8 km hr-1 resulting in approximately five seconds of data acquisition per plot. This amount of time resulted in approximately 25-30 condensed and balanced sample values per plot per parameter (i.e. laser, GPS, Greenseeker®, etc.). After removal superfluous data associated with the power cycling, approximately four to five averaged readings per meter were assigned to each AOI. Rate of travel was dictated by the time necessary to acquire two samples with the CROPSCAN and the more extended data output time of this sensor as compared to others used. As previously stated, each sample required two to three seconds so five seconds were necessary to acquire both samples within the plot length. Length of data acquisition time per plot varied less than one second.

The sensor array measured approximately 25 cm wide and 45 cm from front to back with the Greenseeker® radiometer located most forward and the ultrasonic proximal sensors located at the rear. The GPS was oriented approximately 75 cm to the rear of the ultrasonic sensors and approximately 45 cm right of center. This offset was accounted for in subsequent data parsing. The offset among sensors required that initiation and termination of sensor logging be timed to ensure that all vegetation measurement sensors were above the AOI while logging the data.

Wheat Experiment: Site, Design, and Management

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° N, 96.99° 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. A Hege 500 cone planter grain drill (Hege Equipment Inc., Colwich, KS) was used for planting wheat in autumn 2013, and data was collected in the spring 2014. Approximately 1200 (1.5 x 3 m) plots of 500 wheat varieties were planted as part of variety selection trials. These were arranged in completely randomized block design (CRBD) with two replications.

The second wheat experiment was initiated at the Noble Foundation Unit 3 Farm in Ardmore, OK (34.17° N, 97.08° 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 comprised of 50 wheat varieties. A Hege 500 cone planter grain drill was also used for planting wheat in 2013. Between the two wheat trials, there were seven data collection events occurring from February to April 2014.

Physical Measurements: Wheat Experiment

Wheat biomass for both experiments was estimated by hand clipping one 0.16 m2 quadrat per plot to a 2.5-cm stubble height. Samples were dried in a forced draft oven at 50°C for five days prior to weighing and are reported as kg DM ha-1.

Sensor Height, Spectral, and Spatial Measurements: Wheat Experiment

Sensor data was collected from the wheat trials using a gasoline-powered Spider high-clearance tractor (LeeAgra, Inc., Lubbock, TX) at a ground speed of approximately 1.6-3.2 km h-1 (Fig.2.2). 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 initially powered using the onboard, factory installed, 12 V power supply. For convenience this was later modified to use an independent 12 V power source to power all sensors. Upon restarting the tractor engine a momentary power deficit would occur and required re-initializing the sensor system. The same GPS with OmniStar XP GNSS positioning as described in the alfalfa and bermudagrass trial was implemented to acquire spatial data for all sensor readings. The GPS was configured to output data at a rate of 10 Hz such that multiple locations could be recorded within each plot.

Height was measured using two single 660 nm single beam time of flight laser distance sensors as well as a 120 MHz ultrasonic sensor. These sensors were the same make and model of those used in the alfalfa-bermudagrass experiment. All height sensors were calibrated at a bare ground surface and a 74 cm maximum in the same manner as those used in the alfalfa and bermudagrass experiment as well. All height data were acquired at a rate of 10 Hz and all sensors were configured to collect data centered on a 0.02-m2 area. A Greenseeker® was employed to collect NDVI at rate of 10 Hz for each plot. The passive radiometer (CROPSCAN) was not used on the wheat experiments.

Transport and Temporal Logistics: Wheat Experiment

The sensor array used in the wheat trials measured approximately 20 cm long by 10 cm wide. As was previously described in the alfalfa and bermudagrass experiment, it was necessary to ensure all sensors were above the plot prior to data acquisition initiation and termination. Alley identifiers were assigned during the time spent crossing the alley areas and until all sensors were above the subsequent AOI, whereas plot identifiers were assigned to the incoming data.

Each plot was driven across at 1.6-3.2 km hr-1 resulting in approximately three seconds of data acquisition per plot and due to the fact a delay buffer of approximately one second was allowed at the beginning and end of each plot. This amount of time provided approximately 25-30 readings per plot per parameter (i.e. Laser, Ultrasonic, Greenseeker®). Variability in the length of data acquisition time per plot occurred but was similar to the cart configuration in the alfalfa and bermudagrass experiment and only existed on the order of less than one second.

Data Acquisition Hardware: All Experiments

For all experiments, analog data from the height measurement sensors were acquired using a data acquisition module (DAQ). Laser sensors were configured via a current loop to operate at a range of 0 to 5 VDC and were connected directly to the DAQ for voltage output. The 120 MHz ultrasonic sensor was configured to operate at a range of 0 to 5 VDC, and voltage readings were directly output to the DAQ. The 240 MHz ultrasonic sensor was operated at a range of 0 to 10 VDC and voltage readings were directly output to the DAQ. From the DAQ, all analog data were transferred as digital output to a laptop computer for the alfalfa and bermudagrass trial and ruggedized tablet computer in the wheat trials via USB connection.

Data from the Greenseeker® radiometer was output directly to the tablet and laptop via serial connection as NDVI values, which were generated by the autonomous radiometer processor. CROPSCAN readings were acquired and stored in the autonomous memory contained within the radiometer hardware.. It was not possible to insert plot markers into data from the CROPSCAN as it was necessary for the power source in this unit to remain autonomous and operational function could only be achieved through use of the factory provided software. However, it was possible to operate this software simultaneously on the same laptop, which was used for all other data acquisition. Agrilogger was developed to utilize a sampling logic which resulted in only the user-specified rate of data acquisition to take place. All data was written to a single log file at the user-specified rate. In contrast, WinWedge Pro© (WinWedge Pro©; TAL Technologies Inc., Philadelphia, PA), captured all data from incoming streams at rates dictated by the transmitting hardware. When using WinWedge Pro©, it was necessary to run multiple instances of the software simultaneously, one for each data stream (i.e. DAQ, GPS, and Greenseeker®). Each instance of the software produced one log file for the data stream being acquired, which resulted in multiple output files for each data collection event. The power cycling switch used for plot delineation when acquiring data with WinWedge Pro© at no point interrupted data streams. The power was cycled on such that sensor readings were acquired and null readings were acquired when power was cycled off. These areas of null values signified non-plot areas.

Figure 2.2 Spyder used for transport of sensors across wheat experiments shown with sensor array containing A. GPS, B. Laser and Ultrasonic Sensors, C. Greenseeker, and D. Start and Stop trigger markers for array field of view extent.

This strategy required combining the data from all streams post-processing. AgriLogger enabled the user to insert identifiers real-time as data were acquired. The identifiers used to delineate plot areas from non-plot areas were inserted with a mouse click or touch-screen button.

As previously stated, data acquired from the CROPSCAN were written to the autonomous storage capabilities contained within the unit. Utilization of factory included software application was necessary for post-processing reflectance data. This application produced one log file which could then be combined with data from all other sensors at post-processing based on sampling rate per plot and time stamp.

Data Post-Processing

For both WinWedge Pro© and Agrilogger, time and date fields (based on the laptop clock) were inserted into the data streams for each record received at the application level. This allowed for quality control and the ability to combine data during post-processing when using WinWedge Pro©. Combining log files produced when using WinWedge Pro© was achieved through implementation of a custom post-processing application (DataProcessing). The primary function of the DataProcessing application was averaging data to a desired rate (i.e., 5 Hz, 10 Hz, etc.) so as to balance the number of sensor readings across the sensors and reduce the data to a more manageable volume. The averaging was achieved by utilization of the aforementioned time stamp which had been inserted for each record. After the data were combined, it was output to a text file which contained the combined sensor data at the specified averaging interval (i.e., 5 Hz, 10 Hz, etc.). The output file from the DataProcessing software was then manually edited by attaching range and row identifiers to plot areas. These plot areas were delineated based on the aforementioned null values. The non-plot areas were manually removed from the data, leaving only the range and row identified plot areas. These plot areas could then be assigned a unique plot identifier.

Data acquired using AgriLogger was also manually edited to remove non-plot areas. Due to the user control and plot identification features provided in this software application, the magnitude of the data contained in the single output file were of a much smaller scale than that output by WinWedge Pro©. This was due to the sampling logic data acquisition strategy implemented in AgriLogger as opposed to the constant uncontrolled streaming of data with WinWedge Pro©. A user-specified sampling rate allowed for data acquisition at rates of up to 20 Hz and output of all parameters to a single log file. No post-processing application was necessary for reduction of the data through averaging.

Post-processing data transformation was performed on laser measurements as calibrations produced readings which were inversely proportional to the height of measured vegetation. Laser readings were subtracted from the calibrated maximum reading (signifying the greatest distance from the sensor). This transformed the data to a directly varying scale which agreed with the directly varying relationships between vegetation height and readings from ultrasonic sensors. Both ultrasonic and laser readings were converted to cm values based on the minimum and maximum calibration heights at post-processing.

Data Analysis: All Experiments

Sensor readings were examined for correlation to physically-measured height and destructively-measured DM (Pilloid and Arkle, 2013; Golodets et al.,2013; Brownell et al.,2012). The combination of output from multiple sensors as constituents of a predictive model for biomass was also examined. Comparisons were examined for the accuracy in estimation of height and DM for sensor models versus physical measurements performed. It must be noted that destructive harvest methods differed between the alfalfa-bermudagrass and the wheat experiments. Due to the 2.5-cm difference in harvest height, data analyses for biomass were performed based on harvest method and species for model construction. Additionally, the relationship between forage harvester and quadrat measurements of forage biomass was examined by regression analysis using SAS PROC REG (SAS, 2012).

Correlation: Sensor Measurements to Physical Measurements

Physical and sensor measurement methods were examined for correlation to vegetative mass on a DM basis as well as sensor measurements to measured canopy height. These analyses were performed using SAS PROC CORR (SAS, 2012). Data used for model construction were included for the examination of correlation between sensor measurements and physical measurements.

Model Construction

Data were split into model construction and validation sets. This division was implemented to ensure the entire range of the data would be represented in both. Two hundred-twelve samples were used to generate estimation models for alfalfa only, with a validation set containing 89 samples. Seventy-eight samples were used to construct the bermudagrass only model with 32 validation samples. Wheat biomass models were constructed from 193 samples and 97 validation samples. Since no physically-measured canopy height data was collected for wheat, no canopy height estimation models were generated. Canopy height estimation models for the alfalfa and bermudagrass trial were constructed on a vegetation composition category basis, which consisted of individual species (alfalfa, bermudagrass), mixtures of the two (MIX), and across the entirety of the alfalfa and bermudagrass experiment data (ALL). The MIX group of data from the alfalfa and bermudagrass trial was comprised of sampled verified plots having botanical compositions ranging from 80% alfalfa:20% bermudagrass to 20% alfalfa:80% bermudagrass, (n=1002 for modeling and n=581 for validation).

Estimation models were constructed using partial least squares (PLS) regression analyses (SAS PROC PLS) with CVTEST for selection of simplest models (SAS, 2012; Luo and Wang; 2014, Wuerschun et al, 2014; Chen and Zhu, 2013). Laser and ultrasonic sensor outputs as well as NDVI from the Greenseeker® and seven spectral bands from the CROPSCAN were examined for inclusion in sensor based biomass estimation models. Laser and ultrasonic data were examined in the same manner for canopy height modeling.

Parameters included in biomass and canopy height estimation models were selected by evaluation of Variable Importance Plot (VIP) values output from SAS PROC PLS using the plots=(parmprofiles vip) option, as a filter measure (Wold et al, 1993) (Table 2.1). These scores represent the contribution of a variable as a predictor due to the amount of variance explained and can be viewed as a percentage in relation to one another when a number of predictor variables are simultaneously examined (Wold et al, 1993). All components with VIP scores less than 1 were deleted from the final models for biomass and canopy height (Mehmood et al, 2012; Chong and Jun, 2005; Gosselin et al, 2010). 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.

Table 2.1. Variable Importance Plot (VIP) scores for sensor parameters considered for model inclusion †From Greenseeker®, ‡From CROPSCAN, for modeling alfalfa and bermudagrass biomass.

Sensor measurement	**VIP**	
	DM	**Canopy height**
Laser	1.37	1.08
120 MHz sonic	1.32	1.01
240 MHz sonic	1.11	0.95
NDVI†	1.10	
690 nm‡	0.90	
650 nm‡	0.83	
710 nm‡	0.74	
590 nm‡	0.74	
450 nm‡	0.72	
520 nm‡	0.71	
570 nm‡	0.70	
530 nm‡	0.69	
780 nm‡	0.68	
900 nm‡	0.66	

Upon deletion of less contributive variables, PLS models were again constructed using cross-validation (CVTEST option) with a 20-fold block training set (CV block=20) and the SAS default of 1000 permutations (SAS, 2012). Subsequently a randomly selected block of twenty observations provided cross validation analyses for model training 1000 times for construction of each model. The parameter estimates produced from these analyses were then employed in an equation (models) for calculation of biomass and canopy height estimates (Table 2.2). Botanical composition based canopy height models included the laser and the 120 MHz ultrasonic (VIP scores > 1).

Evaluation of Accuracy in Model Estimation for Biomass and Canopy Height

Regression analyses for canopy height and biomass estimations were performed to evaluate relationships between measured and estimated values using SAS PROC REG for samples from the

Table 2.2. Dry biomass estimation model label key for sensor and physical measures for the alfalfa bermudagrass experiment and the wheat experiment with notation of specifies specific models and number of sensor inputs for each model..

Model number	Estimate	Species specific	Number of sensors
1	Dry biomass	Y	3
3	Dry biomass	Y	2
5	Dry biomass	Y	Meter stick
6	Dry biomass	N	Meter stick
7	Dry biomass	N	Plate meter
8	Canopy height	Y	2
9	Canopy height	N	2

validation data only (SAS, 2012). Additionally, accuracy of estimation models was evaluated on a percent basis by calculating the by sample mean percent error (MPE) (Equation 2.1):

$$\text{Mean Percent Error} = \text{Mean} \sum_{n}^{1} \frac{|\text{Estimate} - \text{Measured}|}{\text{Measured Dry Mass}} \qquad \text{(Equation 2.1)}$$

where E_t is the biomass estimate for the tth plot using the method of interest, M_t is the measured biomass of the tth plot using the harvest method (i.e., the accepted standard), and n is the number of plots measured.

An Error, Consistency, and Mean Agreement (ECMA) scoring system was calculated for ranking and comparison of model estimation accuracy. Calculation of this scoring system considered agreement of measured and corresponding estimated means, the by sample error estimation, and the repeatability of the error across samples in a category. The ranking calculation was compiled such that higher index scores represented more accurate estimation based on mean agreement, error, and the consistent nature of the error. The score included model error consistency (standard deviation of percent error, S_{PE}), accuracy (mean of by sample percent error, MPE), and the agreement of the mean of measured compared to mean of estimated values (R^2 of estimate to measured, as well as difference in mean of estimate 'E' and measured 'M') (Equation 2.2).

$$\mathrm{ECMA} = \frac{\left(\frac{\text{Coefficient of determination for estimate by measured}}{|\text{estimate mean} - \text{measured mean}|}\right)}{\text{mean percent error} * \text{standard deviation of percent error}} \qquad \text{(Equation 2.2)}$$

Least significant difference (LSD) groupings (α=0.05) were compared among plots grouped according to destructively-measured biomass and physically measured canopy height using the biomass and canopy height estimation models as a post-hoc analysis of accuracy (validation samples only were used in this comparison). This was done to illustrate the efficacy of using biomass or canopy height estimations calculated from sensor readings in place of destructive harvesting methods or physical height measurements for trial evaluations. Biomass comparisons groups were delineated in 1.10 t ha-1 increments from 0 to 7.72 t ha-1. Canopy height comparisons were based on 10 physically-measured canopy height classes at ten centimeter increments. These comparisons were performed using PROC MIXED (SAS, 2012 in combination with the PDMIX800 macro (Saxton, 1998; Lauriault et al, 2013).

IV. Findings

Correlation

Laser-estimated height measurements were the most correlated to physically-measured canopy height for all examinations (r = 0.88 bermudagrass - 0.78 MIX). Laser measurements were the most correlated to destructively-sampled biomass as well (r = 0.88 bermudagrass - 0.80 alfalfa). Additionally, NDVI measured using the Greenseeker® was most correlated to biomass (r = 0.75 - 0.62) for all spectral data examined (Table 2.3). Additionally, regression analysis of the harvester collected to quadrat collected biomass measurements yielded results showing quadrat harvests to produce AOI DM estimates on average 5% greater than measurements acquired using the harvester.

Modeling Analyses: Variable Inclusion Selection

All height sensor parameters were associated with VIP values greater than the exclusionary threshold of 1 (Wold et al., 1993; Mehmood et al., 2012; Chong and Jun, 2005; Gosselin et al., 2010) for both biomass and canopy height. The VIP values were greater for the 120 MHz ultrasonic sensor than for

Table 2.3. Pearson coefficients for sensor collected parameters correlated to physical measures of bermudagrass, alfalfa, wheat and a mixture of alfalfa and bermudasgrass. †From Greenseeker®, ‡From CROPSCAN.

Sensor measurement	Alfalfa	Bermudagrass	Mix	Wheat
		Destructively measured DM		
Measured height	0.83	0.83	0.82	
Plate meter	0.43	0.48	0.43	
Laser	0.80	0.88	0.86	0.86
120 MHz sonic	0.74	0.87	0.85	0.85
240 MHz sonic	0.75	0.81	0.66	
NDVI†	0.70	0.75	0.72	0.62
450 nm‡	-0.35	-0.53	-0.41	
520 nm‡	-0.33	-0.54	-0.36	
530 nm‡	-0.32	-0.51	-0.32	
570 nm‡	-0.36	-0.50	-0.37	
590 nm‡	-0.41	-0.56	-0.38	
650 nm‡	-0.48	-0.65	-0.51	
690 nm‡	-0.47	-0.63	-0.54	
710 nm‡	-0.45	-0.52	-0.27	
780 nm‡	0.13	0.02	0.32	
900 nm‡	0.08	0.04	0.28	
		Canopy height		
Plate meter	0.11	0.25	0.24	
Laser	0.83	0.88	0.78	
120 MHz sonic	0.76	0.82	0.73	
240 MHz sonic	0.73	0.71	0.68	

the 240 MHz ultrasonic sensor. The 120 MHz ultrasonic sensor was subsequently selected for inclusion in biomass and canopy height model construction. It was apparent while post processing data from the 240 MHz ultrasonic sensor that large areas were resultant output due to loss of echo which likely diminished contribution of this device in enhancing model accuracy. The spectral component NDVI was selected in the biomass model based on VIP values. Data from the CROPSCAN were not employed in the construction of models due to lower VIP scores than that of

NDVI from the Greenseeker®. It is likely data from the CROPSCAN were less contributive to the estimation of biomass as it was implemented from a mobile platform and data were acquired while moving across plots as opposed to a stationary orientation. The CROPSCAN was designed to be used as a stationary passive spectral radiometer but it was desired to, in this research, evaluate the potential contribution of the CROPSCAN as an element of a mobile system.

Modeling Analyses: Biomass and Canopy Height Estimation Model Performance

Laser-only models explained more variation in dependent variable (VDV) for bermudagrass biomass

Table 2.4. Explanation of variation in dependent variable (VDV) from partial least squares regression modeling for dry biomass and canopy height by sensor estimation models and model equations for height (combination ultrasonic and laser model) and biomass (two sensor model: laser and ultrasonic combination, and three sensor model: laser, ultrasonic and NDVI combination). †MIX-Mixture of alfalfa and bermudagrass; ‡ALL-All monoculture and mixed species from the alfalfa and bermudagrass experiment.

	Canopy height	**Plate meter**	**120 Mhz ultrasonic**	**Laser**
DM	VDV	VDV	VDV	VDV
Alfalfa	68.5%	18%	55%	64%
Bermudagrass	69%	23%	75%	78%
Wheat			72%	74%
MIX†	67.8%	19%	73%	73%
	3 sensor model	**3 sensor equation**	**2 sensor model**	**2 sensor equation**
Alfalfa	65.7%	(46.22*Las+47.83(Son*NDVI)	65.5%	(46.9*Las)+(43.13*Son)
Bermudagrass	80.5%	(65.3*Las)+58.3(Son*NDVI)	81%	(65.7*Las)+(49*Son)
Wheat	75%	(118*Las)+108(Son*NDVI)	74%	231*Las
MIX	78.9%	70.5(Las*NDVI)+63.7(Son*NDVI)	78.5%	(61.3*Las)+(53.9*Son)
		Plate meter	**120 Mhz ultrasonic**	**Laser**
Canopy height		VDV	VDV	VDV
Alfalfa		1.2%	57%	69%
Bermudagrass		6.1%	67%	77%
MIX		5.6%	54%	61%
ALL‡		6.1%	55%	64%
			2 sensor model	**2 sensor equation**
Alfalfa			70%	(0.46*Las)+(0.42*Son)
Bermudagrass			77%	1.02*Las
MIX			64%	0.017(Las*Son)
ALL			65%	(0.74*Las)+(0.2*Son)

(78%) and wheat (74%) than did ultrasonic only models for biomass and canopy height (75 and 72%, respectively). Combination models which included laser and ultrasonic improved dependent variable variation explanation in all cases except for wheat biomass (75%)

and bermudagrass canopy height (77%). Inclusion of NDVI for biomass modeling improved dependent variable variation explanation by an additional 1%. Biomass models based on physically-measured canopy height were more effective than others in explanation of dependent variable variation for alfalfa only (68.5%). Plate meter-based models were less effective than others for canopy height and biomass estimation (0 to 6.1% and 18 to 23%, respectively) (Table 2.4). The greatest R^2 observed (0.85) for any estimated to measured biomass relationship was the dual height sensor combination for bermudagrass. Comparison of biomass model estimation based on ECMA scores showed that models which included both height sensors as well as NDVI were more accurate in all cases except for bermudagrass (Table 2.5). The smallest R^2 observed (0.13 to 0.25) in all cases was for the plate meter models. The meter stick measured height model was ranked second for alfalfa biomass estimation and was the only instance of a physical measurement model being ranked in the top two for biomass estimation. Regression of estimated canopy height to measured canopy height using model 9 for bermudagrass produced the greatest R^2 for all cases (0.84). Canopy height estimates in alfalfa and the legume-grass mixture produced R^2 values of 0.61 or less (Table 2.5).

Post Hoc Comparisons:

Sensor Estimation Models and Measured Biomass / Canopy Height Comparisons

Sensor models consistently overestimated small destructively measured biomass values and underestimated large values. Order of mean estimates for measured biomass and sensor-estimated biomass agreed except in the grass-legume mixture. In this case of order inconsistency, only the greatest biomass categories were inconsistent with measured values (> 5.51 t ha-1). The three sensor model (model 1) consistently produced lower biomass estimates than did the dual sensor model (model 3) for all species (Table 2.6).

Sensor models consistently underestimated canopy height for taller measured values but produced estimates within 4 cm of the lowest measured height from models 8 and 9. The only exception in minimum canopy height estimation occurred in MIX model 8 estimates where the estimate was 10 cm lower than measured (Table 2.7).

Table 2.5. Sensor model ranking based on Error, Consistency, and Mean Agreement Score (ECMA) †MPE (0.19), Standard Deviation of MPE (0.36) and R^2 (0.87) for measured were calculated from paired bermudagrass plots. ‡MIX-Mixture of alfalfa and bermudagrass.

Forage type	Measure/ Estimation method	Mean	Mean- percent error (MPE†)	Standard deviation MPE†	R^2 -measured to estimated†	ECMA score
			DM (t ha^{-1})			
Alfalfa	Measured DM	2.36				
Alfalfa	1	2.16	0.31	0.27	0.69	0.150
Alfalfa	5	3.02	0.30	0.24	0.63	0.083
Alfalfa	3	2.36	0.40	0.35	0.68	0.019
Alfalfa	7	2.16	0.53	0.67	0.13	0.005
Alfalfa	6	3.02	0.68	0.53	0.63	0.002
Bermudagrass	Measured DM†	3.33	0.19	0.36	0.87	
Bermudagrass	3	3.41	0.32	0.57	0.85	0.069
Bermudagrass	1	3.45	0.36	0.6	0.81	0.033
Bermudagrass	6	3.54	0.36	0.55	0.82	0.022
Bermudagrass	5	3.98	0.47	0.65	0.82	0.005
Bermudagrass	7	1.9	0.63	0.69	0.25	<0.000
MIX‡	Measured DM	2.15				
MIX	1	1.83	0.30	0.26	0.79	0.035
MIX	3	2.37	0.40	0.52	0.78	0.019
MIX	6	2.76	0.68	0.79	0.55	0.002
MIX	7	1.66	0.48	0.58	0.17	0.001
MIX	5	3.1	0.85	0.91	0.55	0.001
Wheat	Measured DM	2.47				
Wheat	1	2.74	0.41	0.65	0.81	0.013
Wheat	3	3.18	0.63	0.94	0.80	0.002
			Canopy height (cm)			
Alfalfa	Measured height	30.8				
Alfalfa	9	22.5	0.30	0.17	0.61	0.04
Alfalfa	8	21.0	0.33	0.18	0.59	0.03
Bermudagrass	Measured height	36.1				
Bermudagrass	8	29.0	0.21	0.12	0.79	4.05
Bermudagrass	9	26.0	0.28	0.13	0.84	2.29
MIX	Measured height	28.2				
MIX	9	18.5	0.35	0.19	0.57	0.88
MIX	8	7.2	0.77	0.17	0.59	0.21

The LSD values for biomass and height estimation models were greater than those for the measured values. These LSD values indicated more variation within estimates for both canopy height and biomass resulting in overlapping of mean estimate groupings in some cases.

Due to the fact the groupings were based on measured canopy height and measured DM, those measured groups would be expected to express the lowest variation.

Additional error is also likely introduced into the modeled DM mean estimates due to the fact that the destructively measured DM does not capture in entirety the vegetation being sampled by the sensors. This error is illustrated in the stubble height remaining after destructive harvest which is embedded in and accounted for by the sensor readings and subsequently inseparable from the sensor models and sensor based estimations. This type of error could account for instances of over estimation at low biomass levels. Radial growth expansion as vegetation matured as well as under canopy fill-in may account for instances of biomass underestimation.

Biomass Estimation Using Physical Canopy Height Measurements

Canopy height models varied by model and species, generally overestimating at lowest biomass categories and underestimating at highest biomass categories (Table 2.6). Model 6 overestimated whereas model 5 underestimated alfalfa biomass. Both measured height models overestimated bermudagrass biomass except for the greatest measured biomass. Biomass estimates for the mixture for both measured height based models overestimated at lesser values (< 2 t ha-1) and underestimated at greater values (>5 t ha-1).

Plate meter biomass estimation model ordered mean estimates the same as measured for only the alfalfa and consistently overestimated low and underestimated large measured values.

Destructive Biomass Measurement and Model Estimate Variability

Due to the variation associated with destructively-measured biomass, it is unlikely that an estimation strategy based on this method of measure could achieve accuracy or precision in excess of the method

Table 2.6. Mean estimates comparisons and LSD groupings for destructively measured DM and sensor modeled estimates of DM. Uppercase letters denote statistical differences from other categories. †MIX-Mixture of alfalfa and bermudagrass.

Forage Class	**DM class (t ha^{-1})**	**Measured DM (t ha^{-1})**	**Sensor Estimate DM models (t ha^{-1})**	
			1	**3**
Alfalfa	>1.1	0.85E	1.28D	1.5D
Alfalfa	1.1-2.2	1.65D	1.86C	2.09C
Alfalfa	2.2-3.3	2.72C	2.66B	2.89B
Alfalfa	3.3-4.41	3.6B	3.26A	3.45A
Alfalfa	4.41-5.51	4.88A	3.81A	4.01A
LSD		**0.22**	**0.44**	**0.44**
Bermudagrass	>1.1	0.67F	1.45E	1.58D
Bermudagrass	1.1-2.2	1.7E	1.97E	2.08D
Bermudagrass	2.2-3.3	2.96D	2.89D	2.93C
Bermudagrass	3.3-4.41	3.77C	3.8C	3.67C
Bermudagrass	4.41-5.51	4.99B	5.2B	5.02B
Bermudagrass	5.51-6.61	6.97A	6.19A	6.53A
LSD		**0.53**	**0.75**	**0.84**
MIX†	>1.1	0.83G	0.98F	1.53F
MIX	1.1-2.2	1.61F	1.26E	1.82E
MIX	2.2-3.3	2.67E	2.32D	2.84D
MIX	3.3-4.41	3.79D	3.02C	3.45C
MIX	4.41-5.51	4.92C	4.45B	5.03B
MIX	5.51-6.61	6.15B	5.06A	5.56A
MIX	6.61-7.71	7.06A	4.56B	4.94B
LSD		**0.15**	**0.28**	**0.27**
Wheat	>1.1	0.78F	1.51D	1.93D
Wheat	1.1-2.2	1.57E	1.79D	2.27D
Wheat	2.2-3.3	2.76D	2.81C	3.26C
Wheat	3.3-4.41	3.85C	4.33B	4.75B
Wheat	4.41-5.51	4.89B	4.98A	5.28B
Wheat	5.51-6.61	6.25A	5.48A	5.85A
LSD		**0.27**	**0.53**	**0.54**

			Measured height DM Estimate models (t ha^{-1})		
			5	**6**	**7**
Alfalfa	>1.1	0.85E	1.18D	1.81D	1.7D
Alfalfa	1.1-2.2	1.65D	1.72C	2.65C	2.08C
Alfalfa	2.2-3.3	2.72C	2.39B	3.67B	2.31C
Alfalfa	3.3-4.41	3.6B	3.05A	4.68A	2.63B
Alfalfa	4.41-5.51	4.88A	3.51A	5.38A	3.07A
LSD		**0.22**	**0.46**	**0.71**	**0.46**
Bermudagrass	>1.1	0.67F	1.62E	1.44E	1.6B
Bermudagrass	1.1-2.2	1.7E	2.78D	2.47D	1.66B
Bermudagrass	2.2-3.3	2.96D	3.53C	3.14C	1.73B
Bermudagrass	3.3-4.41	3.77C	4.85B	4.31B	2.05B
Bermudagrass	4.41-5.51	4.99B	5.63B	5.01B	2.34A
Bermudagrass	5.51-6.61	6.97A	6.44A	5.73A	2.27B
LSD		**0.53**	**0.97**	**0.86**	**0.62**
MIX	>1.1	0.83G	2.23F	1.98F	1.49C
MIX	1.1-2.2	1.61F	2.88E	2.56E	1.49C
MIX	2.2-3.3	2.67E	3.26D	2.91D	1.9B
MIX	3.3-4.41	3.79D	3.56C	3.17C	1.89B
MIX	4.41-5.51	4.92C	5.46B	4.86B	2.22A
MIX	5.51-6.61	6.15B	5.95A	5.3A	2.1B
MIX	6.61-7.71	7.06A	5.38B	4.79B	2.12B
LSD		**0.15**	**0.36**	**0.32**	**0.25**

upon which it is based. This destructively-measured variability is illustrated by the R^2 of 0.87 from paired visually identical bermudagrass plots included in Table 2.5. A number of factors lead to error associated with machine harvest examples of which include operator performance, height and type of vegetation, and weigh mechanism performance due to environmental variables. The use of a sensor array to estimate biomass is subject to none of the factors in the same way the machine harvest strategy would be. Subsequently, basing the estimation of biomass by sensor populated modeling when constructed from machine harvest weight data will introduce all error associated the machine harvest into the model as well as any error associated with the sensor system. This will suppress the

Table 2.7. Mean estimates for measured canopy height (cm) and sensor model estimates of canopy height (cm). Uppercase letters denote statistical differences from other categories.
† No height data occurred in this range for bermudagrass. ‡MIX-Mixture of alfalfa and bermudagrass.

Forage Class	Height class (cm)	Measured canopy height (cm)	Model 8 (cm)	Model 9(cm)
Alfalfa	>15	12J	16CD	16DE
Alfalfa	15-20	17I	14D	15E
Alfalfa	20-25	21H	16D	18DE
Alfalfa	25-30	27G	16CD	18DE
Alfalfa	30-35	33F	22BC	22CD
Alfalfa	35-40	37E	20BCD	23CD
Alfalfa	40-45	43D	27B	28C
Alfalfa	45-50	47C	26B	29BC
Alfalfa	50-55	53B	32A	35AB
Alfalfa	55-60	57A	35A	38A
LSD		**2**	**6**	**6**
Bermudagrass	>15	14I	13D	11D
Bermudagrass	15-20	16I	13D	11D
Bermudagrass	20-25	21H	17CD	15CD
Bermudagrass	25-30	29G	24BCD	20BCD
Bermudagrass	30-35	31F	25BC	22BC
Bermudagrass	35-40	36E	28B	25B
Bermudagrass	40-45	42D	30B	27B
Bermudagrass	45-50†	*	*	*
Bermudagrass	50-55	54C	43A	39A
Bermudagrass	55-60	57B	47A	43A
Bermudagrass	60+	66A	51A	48A
LSD		**3**	**12**	**10**
MIX‡	>15	12J	2F	13E
MIX	15-20	17I	3F	14E
MIX	20-25	22H	3F	14E
MIX	25-30	27G	5E	16D
MIX	30-35	32F	7D	19C
MIX	35-40	36E	6DE	19C
MIX	40-45	42D	7DE	21C
MIX	45-50	48C	22C	34B
MIX	50-55	52B	27B	38A
MIX	55-60	57A	31A	40A
LSD		**1**	**2**	**3**

accuracy of the modeling due to the fact the number of error terms contributing to the calculation of biomass are from both the machine harvest as well as any associated with the sensors.

V. Conclusions

Using mobile sensor systems for biomass estimation can enable a greater rate of data acquisition than manual canopy height or destructive sampling provided an appropriate software option for data acquisition is employed. Results from this study illustrate quantification of only the canopy height with ultrasonic and laser sensors can provide for biomass estimation models equivalent to and/or more effective than those which include spectral components. This is an important distinction as the cost associated with assimilation of an active spectral radiometer into such a system can greatly increase costs. An increase of approximately 1% in dependent variable variation explanation was contributed to the system at a cost in excess of US$4000. In contrast, height sensors and a DAQ would only incur a total cost of approximately US$1500. Additional costs for consideration would be the pc hardware needed, cost of software, and cost of vehicle for transport of the sensor array.

Additionally, sensor estimates provide equivalent and/or superior estimates when compared to physical canopy height measurement and plate meter biomass estimation methods. It is arguable that the same is the case for collection of sensor-based canopy height data, though a maximum height threshold of accuracy is likely according to the physical limits and configuration of sensors used. Due to the commonly accepted nature of physically measured biomass estimates for research applications, sensor-based estimation strategies which utilize species differentiation in appropriate cases and ultrasonic/laser proximal sensor combinations have, in this research, been illustrated to produce comparable and/or more accurate results. Consideration should also be given to the time savings associated with using a mobile sensor system. During the course of these studies it was noted manhours needed for physical collection of these data (30 hrs rep-1) were greater by a factor of 60 than the time needed to collect data with the sensor system (0.5 hrs). Furthermore, processing of data acquired using AgriLogger reduced man-hour requirements by a factor of 10.

In order for the greatest level of accuracy to be obtained, it is likely necessary to implement specific models for predominant or monoculture species though a general estimation model may produce acceptable estimates for mixed species. It may also be possible to stratify implementation of models based on height measurement. This would allow adjustment of coefficients to accommodate minimum and maximum values which can be estimated imprecisely if only one model curve is applied to the entire range of canopy heights and biomass levels encountered. Further examination of spectral data as a model component may be necessary for other parameters not examined in these experiments. Future examination of additional species is also necessary to develop models for estimating DM across different environments and production systems.

Qualification of relative vegetative performance based on canopy height and/or biomass would also be possible and could contribute to variety selection for plant breeding. Difficulties in system calibration and sensor data conversion to absolute measures could be avoided in a qualitative system. It can also be asserted that results reported for research could be based on sensor-estimated biomass without the expectation of appreciable differences than would be reported from destructively sampled methods or physical measurement based estimates. Estimating biomass without vegetation removal would be useful for plant breeders needing to quantify biomass along with seed yield. In addition, forage mass could be measured prior to and post-grazing to evaluate persistence and production under grazing that currently cannot be done. Ultimately, real-world production management decisions such as stocking rate adjustments or forage harvesting intervals could be made in a much more rapid manner.

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CHAPTER III

Bermudagrass, Wheat, and Tall Fescue Crude Protein Forage Estimation Using Active Spectral and Canopy Height Data Collected from a Mobile Platform

I. Introduction

Forage quality analysis has traditionally been performed through laboratory (Kellems and Church, 1998) and NIRS analysis (Norris et al., 1976). These methods of forage analysis are accepted as accurate and used for livestock feed ration estimation but require a number of days or weeks for results to be delivered. Remote sensing provides an alternative which could provide forage quality estimates with less turn-around time and allow more rapid decision making for stocking rate adjustments or inclusion of a feeding supplement.

II. Review of Literature

The examination of hyperspectral reflectance for indicating nitrogen content in vegetation is somewhat extensive. Estimation of bermudagrass [*Cynodon dactylon* (L.) Pers.] nitrogen content through the use of spectral sensors has been examined by Starks et al., (2004) for multiple wavebands in the 368-1100 nm (nanometer) range and produced estimates with R^2 of 0.76 as compared to laboratory analysis. An R^2 of 0.82 was reported by Starks et al., (2008) for nitrogen concentration to spectral reflectance in the 705-1685 nm range in warm season grass pastures..

Starks and Brown (2010) noted no cultivar specific model offered an advantage in improving estimation accuracy for nitrogen concentrations of three bermudagrass cultivars using hyperspectral reflectance measurements from 350-1125-nm. Guo et al., (2010) observed R^2 values of 0.63 for forage CP (crude protein) estimation when hyperspectral data in the 350-2500 nm was collected in a semi-arid mixed prairie ecosystem. Biewer et al., (2009) examined spectral reflectance for 630-1000 nm range in legume grass swards and reported an R^2 of 0.86 for the relationship of estimated to laboratory analyzed CP. Albayrak (2008) published R^2 values of 0.87 for nitrogen content prediction from spectral reflectance indices which 460 nm, 550nm, 650nm, and 780nm in sainfoin (*Onobrychis sativa* Lam.) pastures. Tang et al., (2004) reported R^2 of 0.70 for CP to hyperspectral reflectance as well as R^2 of 0.65-0.80 for hyperspectral reflectance to nitrogen concentration (Tang et al., 2007) in rice (*Oryza sativa* L.). Zhang et al., (2012) observed R^2 of 0.96 for CP estimates from spectral data collected in the 200-1100 nm region when regressed with laboratory analysis in rice. Hyperspectral data has also been examined for correlation to nitrogen status in wheat (*Triticum aestivum* L.) (R^2=0.44) and corn (*Zea mays* L.) (R^2=0.72) (Chen et al., 2010). Eitel et al., (2008) reported NDVI (normalized difference vegetative index) to be only marginally correlated to chlorophyll concentration in dryland wheat (R^2=0.46). Feng et al., (2014) reported R^2 of 0.85 for wheat leaf nitrogen concentration and spectral reflectance at 755 and 680 nm. Fitzgerald et al., (2010) examined the correlation of canopy chlorophyll content index to canopy nitrogen content in wheat and observed an R^2 of 0.97. Govind et al., (2005) found broad band spectral indices to be more sensitive to plant nitrogen content in wheat than hyperspectral reflectance indices. A limiting factor in utilizing the passive hyperspectral instruments implemented in these studies requires the need for consistent lighting conditions and small windows of optimal sampling conditions in the field. As a number of studies have shown, reflectance at visible to NIR (near infrared) spectra are highly correlated to nitrogen content in vegetation. It is intuitive that spectral sensing instrumentation which does not rely on environmentally variable lighting conditions and can acquire reflectance measurements will potentially provide a robust method for leaf nitrogen estimation. Erdle et al., (2011) recorded R^2

values up to 0.96 for active spectral sensors acquiring reflectance measurements at 730nm and 760nm when regressed with wheat leaf nitrogen. Cabrera-Bosquet et al., (2011) reported R^2 from 0.47 to 0.71 between NDVI and above ground nitrogen content in wheat. Although a significant body of literature exists considering the relationship of spectral reflectance to vegetative nitrogen status, examination of active spectral sensing from a mobile platform for development of estimation models to predict forage crude protein have not been validated.

Objective

The objective of this project was to construct a predictive model from visible to NIR hyperspectral data from passive instrumentation and narrow band based RED to NIR spectral models from active sensors to approximate CP in bermudagrass ('Midland 99'). The strategy employed included three components for constructing hyperspectral predictive models for CP: 1. Individual wavelength based model, 2.Eleven (10 nm wide) Band Model, 3. Three band model (69nm, 19nm, and 19nm wide). Additionally bermudagrass, tall fescue, and wheat CP estimation models were constructed using NDVI calculated from active sensor measurements.

III. Methodology

Bermudagrass Wheat and Tall Fescue Experiment Locations Descriptions and Design

The bermudagrass experiment was conducted at the Noble Foundation Red River Research and Demonstration Farm near Burneyville, OK (33.88° N, 97.28° 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 value of 64 g P kg^{-1}, 52 g K kg^{-1} (amended with 178 kg ha^{-1} 0-0-60), and pH of 6.3. The trial consisted of twenty eight plots per trial year (3.0 m x 6 m) treated with seven levels of N fertilizer ranging from 0 to 224 kg N ha^{-1} yr^{-1} in both 2012 and

2013. The 3.0 m width of these plots allow for splitting of the plots into two near identical side-by-side 1.5 m wide plots for increased replication which resulted in fifty-six sub-plots. This resulted in four replications of a randomized complete block design (RCBD) with a split plot arrangement. The nitrogen applications were applied to ensure a range of CP, which would allow for viable trend analysis and model construction. These plots were sampled for hyperspectral data once in 2013 and 3 times per year in both 2013 and 2014 for NDVI.

Two wheat experiments were examined during the course of this study. The first wheat experiment was initiated at the Noble Foundation Unit 3 Farm in Ardmore, OK (34.17° N, 97.08° 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 80 (1.5 x 6 m) plots comprised of treated with seven levels of N fertilizer ranging from 0 to 224 kg N ha^{-1} yr^{-1} in 2014. Treatments were arranged in eight replications of a randomized complete block design (RCBD). A Hege 500 cone planter grain drill (Hege Equipment Inc., Colwich, KS) was used for planting wheat in 2014. As in the bermudagrass experiment, nitrogen applications were applied to ensure a range of CP, which would allow for viable trend analysis and model construction. Data was collected four times from October of 2014 to March of 2015. The second wheat experiment was initiated at the Noble Foundation Dupy Farm near Gene Autry, OK (34.29° N, 96.99° W; elevation 220 m.). The soils are characterized as Dale silt loam with pH of 7.3 and N-nitrate, P, and K of 11, 42, and 198 g kg-1, respectively. A Hege 500 cone planter grain drill (Hege Equipment Inc., Colwich, KS) was used for planting wheat in autumn 2014, and data was collected in November, December and January from sixty randomly selected plots. Three-hundred and fifty (1.5 x 3 m) plots of 70 wheat varieties were planted as part of variety selection trials. These were arranged in completely randomized block design (CRBD) with five replications.

The tall fescue experiment was initiated at the Noble Foundation Unit 3 Farm in Ardmore, OK (34.17° N, 97.08° 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 7, 25, and 55 g kg^{-1}, respectively. This trial contained 40 (1.5 x 6 m) plots treated with seven levels of N fertilizer ranging from 0 to 224 kg N ha^{-1} yr^{-1} in 2014. Treatments were arranged in four replications of a randomized complete block design (RCBD). Tall fescue plots were planted into a conventionally prepared seedbed using a Great Plains 3P605NT sod seeder (Great Plains Ag, Salina, KS). Data was collected seven times from April of 2014 to March of 2015.

For all experiments samples for laboratory NIRS FQA (forage quality analysis) were acquired by hand clipping one 0.16 m^2 (wheat and tall fescue) and two 0.11 m^2 (bermudagrass) quadrat per plot to a 2.5-cm stubble height. Samples were dried in a forced draft oven at 50°C for five days prior to grinding and submission for analysis to the Samuel Roberts Noble Foundation NIRS laboratory (Ardmore, OK).

Hyperspectral Data Collection: Bermudagrass Experiment

Hyperspectral irradiance measurements were acquired at the canopy level for bermudagrass plots using a JAZ© passive hyperspectral spectrometer (Ocean Optics, Dunedin, FL) at 0.3 nm resolution from 340-1030 nm. The plots were each sampled six times for hyperspectral data using a JAZ field hyperspectral radiometer with three samples evenly spaced the length of the plot on the north 1.5m (north ½ width) and three on the south 1.5m (south ½ width). All hyperspectral data and FQA samples were collected within one hour at approximately one o'clock pm CST on a day which was characterized by very little wind and virtually no cloud cover (11-1-2013). Despite the autumn date of data collection no frost damage had yet been incurred by the bermudagrass and the vegetation was photo-synthetically viable. This late date was chosen as the air temperatures were mild enough to alleviate an over-heating issue which had rendered data from previous collection events unusable. Despite this precaution data for the fourth replication was not recorded due to equipment failure. This was not discovered until after leaving the location and subsequently acquisition of this data was not possible as replication of the calibration and environmental conditions would have not been possible. The Jaz fibers were attached to a metal rod at approximately 122 cm above ground surface as to establish a consistent sensing height. The sensing footprint was approximately 0.11 m^2.

Active Spectral and Canopy Height Data Collection Bermudagrass, Wheat and Tall fescue Experiments

In the bermudagrass experiment, A ground-based mobile platform was utilized for moving sensors across the trial areas using an electric golf cart (the golf cart was selected due to minimal suspension travel) fitted with drop spindles and oversized tires spaced at 1 m, to minimize contact with the biomass contained within the plot area (1.5 m x 6 m). The cart was custom-fitted with a mast extending from the front upon which sensors were attached. A single deep cycle 12 VDC marine battery was added to the cart and served as the power source for all sensors. Power and/or accessory power to all sensors was routed through a system power cycle switch by which all active data acquisition could be initiated or terminated simultaneously. A Greenseeker® (Trimble, Sunnyvale, CA) was employed to collect NDVI and IRVI (Infrared Vegetative Index) at rate of 20 Hz from each plot. Additionally, a GPS with OmniStar XP GNSS positioning (repeatability <10 cm, 95% CEP) was implemented to acquire position data for all sensor readings. The GPS was configured to output spatial data at a rate of 10 Hz such that multiple locations could be recorded within each plot. Height was measured using single beam 660 nm time of flight laser distance sensors (Pittman et al., 2015). Sensor data was collected from the wheat and tall fescue experiements using a gasoline-powered Spider high-clearance tractor (LeeAgra, Inc., Lubbock, TX) at a ground speed of approximately 1.6-3.2 km h-1. The factory-installed spray mast attached to the front of the tractor was converted to a manifold configuration to accommodate sensors. A 12V deep cycle marine battery was also employed on this platform as the powers source for sensors. The Greenseeker® was also employed on this platform to collect NDVI at rate of 10 Hz for each plot. The same GPS with OmniStar XP GNSS positioning as described in the bermudagrass experiment was implemented to acquire spatial data for all sensor readings. The GPS was configured to output data at a rate of 10 Hz such that multiple locations could be recorded within each plot.

Data Acquisition and Post Processing

A white standard was sampled after every third sample for irradiance corrections in post processing of hyperspectral data. A total of 63 samples were retained for analysis which included only three samples from fourth replication due to equipment failure and three omissions from reps 1, 2 and 3 due to corrupted data. Data were processed using Spectra Suite Software© (Ocean Optics, Dunedin, FL) with the white standard taken every third sample serving as the illumination correction standard. Dark standards for all processing were extracted from the initial calibration as no baseline shift was present. All spectral data were reported as relative reflectance values. All decimal wavelengths were averaged such as to provide one irradiance value per wavelength. For all active spectral experiments, all streams of data were captured real-time using AgriLogger or WinWedge Pro (Pittman et al., 2015) (WinWedge Pro©; TAL Technologies Inc., Philadelphia, PA). These software applications were not used simultaneously for concurrent data collection, and WinWedge Pro© was only used to capture data in initial stages of the bermudagrass experiment. Agrilogger was developed to allow only the user-specified rate of data acquisition to take place, while WinWedge Pro© captured all data from incoming streams at rates dictated by the transmitting hardware. Multiple instances of the application run simultaneously were necessary when using WinWedge Pro© where as Agrilogger was capable of collecting data from all incoming streams. AgriLogger enabled the user to insert identifiers real-time as data were acquired. The identifiers used to delineate plot areas from non-plot areas were inserted with a mouse click or touch-screen button and recorded on the single combined output file produced by Agrilogger. No plot delimiters could be inserted when using WinWedge Pro©, subsequently cycling of power to sensors was necessary in order to delineate plot areas via insertion of null values. Additionally, 1 output file was produced for each instance of the application running resulting in multiple output files for each data collection event when using WinWedge Pro©. The single file produced when using Agrilogger was parsed based on spatial data with the recorded plot numbers being used as a quality control check measure. Data collected using WinWedge Pro© was parsed via spatial data with the occurrence of null values used as a quality control check. All NDVI, spatial and canopy height values were averaged on a by-plot basis to provide one composite value for each plot. Canopy height values were approximated using the method developed by Pittman et al. (2015).

Data Analysis and Model Construction

The data were split into a modeling data set and validation data set for each experiment. The data were sorted based on CP prior to splitting to ensure both modeling and validation sets contained consistent distributions of the CP range encountered. Modeling data for the hyperspectral bermudagrass experiment were examined for correlation to CP using SAS PROC CORR (SAS, 2012). Variable importance plot scores (VIP) (Table 3.1) for hyperspectral data in relation to Pearson Coefficient (CP) were generated using partial least squares regression (SAS PROC PLS) (SAS, 2012). The PROC PLS analysis of hyperspectral data allowed delineation the spectral areas which explained the most variation in CP. The product of the VIP and PC (VP Score) was used as a scoring mechanism to rank wavelength appropriateness for inclusion in predictive models (Table 3.1). The lower limit for model inclusion was set at a VP score above 0.68 as this provided inclusion of 3 distinct tightly grouped spectral regions. Below this score no consistent pattern of regional scoring occurred. PROC PLS was then used to construct models using leave-one-out cross validation with 1000 random permutations. Three models were constructed which included an individual wavelength based model, a ten nanometer band model and a spectral region band model (Table 3.2). The ten nanometer band model and spectral region model were based on averaged irradiance across the appropriate spectral region. Predictive models were constructed from 42 samples. Potential predictive accuracy for each model was evaluated based on the percent of variation explained by modeled variables for the dependent variable (VDV). Parameter coefficients were obtained from the PROC PLS output using the VARSS option. These coefficients were employed to calculate non scaled

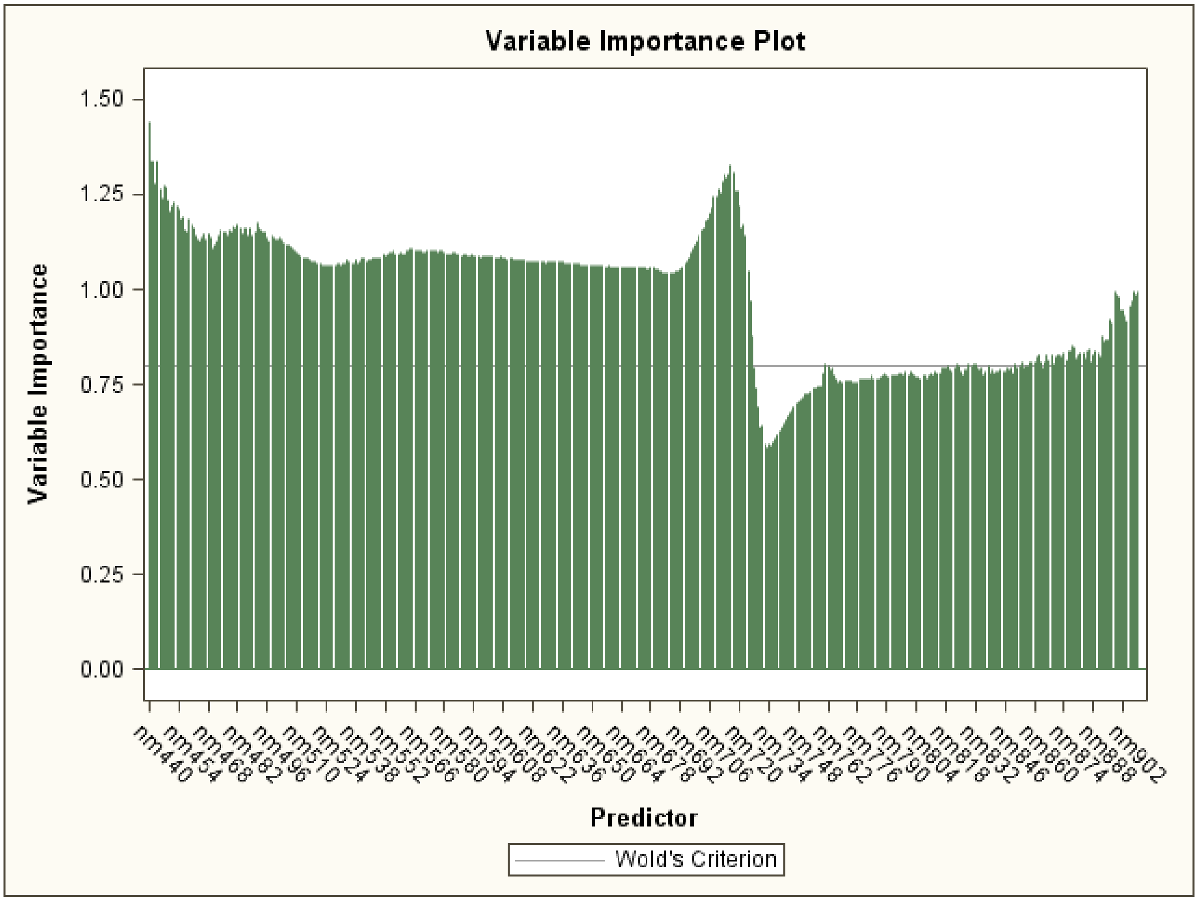

Figure 3.1.Variable Importance Plot output from PROC PLS (SAS, 2012) for hyperspectral reflectance data collected from bermudagrass for CP estimation model variable selection. Spikes in the pattern indicate higher contribution in explanation of dependent variable variation (CP) and are more likely to contribute to accurate modeling. All variables with scores occurring beneath the exclusionary criterion line of 0.8 do not contribute significantly to the model.

estimates from the calibration data and a conversion relationship was defined as regression equation. This combination of the coefficients and conversion equation (Table 3.3) were used to estimate CP for the remaining data not used in model construction (21 samples). Regression (PROC REG; SAS, 2012) was used to evaluate the relationship of the CP estimates to the laboratory measured CP. Mean percent error (MPE) was between estimated and laboratory analyzed CP was calculated to illustrate the error associated with estimates. PROC MIXED was used to evaluate the nature of the relationship between CP and NDVI as well as IRVI for departure from linearity for all experiments (SAS, 2012).

Table 3.1.Pearson coefficients, Variable importance scores (VIP), and the product of VIP and PC (VP Score) for spectral reflectance for three CP estimation models in bermudagrass consisting of individual wavelengths in wide spectral regions, eleven 10nm bands, and three variable width regional bands.

Wide Spectral Region Model				Eleven 10nm Band Model				Variable Bandwidth Model			
Wavelength	PC	VIP	VP	Wavelength	PC	VIP	VP	Band	PC	VIP	VP
440	-0.697	1.087	0.759	495	-0.768	0.913	0.701	440-449	-0.728	0.971	0.707
441	-0.715	0.975	0.698	496	-0.773	0.918	0.71	450-459	-0.754	0.936	0.706
442	-0.719	0.993	0.714	497	-0.776	0.923	0.716	460-469	-0.768	0.912	0.7
443	-0.734	0.96	0.705	498	-0.771	0.914	0.705	470-479	-0.771	0.904	0.697
444	-0.722	1.017	0.735	499	-0.773	0.916	0.708	480-489	-0.767	0.909	0.697
445	-0.732	0.946	0.693	500	-0.776	0.916	0.711	490-499	-0.77	0.913	0.703
446	-0.738	0.925	0.683	501	-0.776	0.915	0.71	500-509	-0.781	0.917	0.716
447	-0.732	0.948	0.695	502	-0.775	0.91	0.705	560-569	-0.82	0.991	0.813
448	-0.736	0.965	0.711	503	-0.777	0.913	0.71	570-579	-0.831	1.051	0.873
449	-0.743	0.946	0.703	504	-0.78	0.917	0.715	700-709	-0.844	1.088	0.919
450	-0.75	0.939	0.704	505	-0.782	0.92	0.72	710-719	-0.793	1.246	0.988
451	-0.748	0.951	0.711	506	-0.782	0.919	0.719				
452	-0.745	0.955	0.712	507	-0.783	0.92	0.721				
453	-0.748	0.961	0.72	508	-0.785	0.92	0.723				
454	-0.75	0.937	0.703	509	-0.787	0.925	0.728				
455	-0.754	0.926	0.699	560	-0.811	0.968	0.785				
456	-0.754	0.937	0.707	561	-0.813	0.969	0.788				
457	-0.761	0.921	0.701	562	-0.817	0.984	0.805				
458	-0.765	0.916	0.701	563	-0.818	0.985	0.806				
459	-0.757	0.928	0.703	564	-0.82	0.991	0.813				
460	-0.762	0.923	0.704	565	-0.822	0.996	0.819				
461	-0.762	0.918	0.7	566	-0.823	0.999	0.822				
462	-0.766	0.911	0.699	567	-0.824	1.005	0.828				
463	-0.771	0.909	0.701	568	-0.825	1.01	0.834				
464	-0.772	0.904	0.699	569	-0.827	1.017	0.841				
465	-0.768	0.908	0.698	570	-0.826	1.012	0.836				
466	-0.767	0.914	0.701	571	-0.828	1.025	0.849				
467	-0.77	0.909	0.7	572	-0.829	1.037	0.86				
468	-0.765	0.92	0.705	573	-0.829	1.041	0.864				
469	-0.768	0.906	0.696	574	-0.83	1.048	0.87				
470	-0.776	0.899	0.698	575	-0.832	1.061	0.883				
471	-0.775	0.902	0.7	576	-0.832	1.066	0.888				
472	-0.774	0.904	0.7	577	-0.832	1.069	0.89				
473	-0.771	0.905	0.698	578	-0.833	1.078	0.898				
474	-0.768	0.908	0.697	579	-0.834	1.079	0.9				
475	-0.768	0.907	0.697	700	-0.837	1.121	0.938				
476	-0.768	0.905	0.695	701	-0.84	1.119	0.94				
477	-0.772	0.906	0.699	702	-0.843	1.12	0.944				
478	-0.767	0.906	0.695	703	-0.843	1.101	0.928				
479	-0.769	0.906	0.697	704	-0.845	1.102	0.932				
480	-0.765	0.906	0.693	705	-0.843	1.081	0.912				
481	-0.766	0.907	0.695	706	-0.843	1.081	0.912				
482	-0.763	0.907	0.693	707	-0.842	1.081	0.911				
483	-0.765	0.909	0.696	708	-0.843	1.093	0.922				
484	-0.769	0.911	0.702	709	-0.838	1.087	0.911				
485	-0.765	0.909	0.696	710	-0.836	1.097	0.918				
486	-0.766	0.907	0.695	711	-0.83	1.101	0.914				
487	-0.77	0.915	0.705	712	-0.824	1.13	0.932				
488	-0.766	0.909	0.697	713	-0.816	1.158	0.946				
489	-0.771	0.914	0.705	714	-0.803	1.205	0.968				
490	-0.769	0.913	0.703	715	-0.789	1.267	0.999				
491	-0.763	0.908	0.693	716	-0.775	1.322	1.025				
492	-0.766	0.91	0.697	717	-0.754	1.415	1.068				
493	-0.768	0.91	0.699	718	-0.719	1.577	1.134				
494	-0.768	0.912	0.701	719	-0.69	1.69	1.167				

PROC PLS was implemented in the same way for NDVI model construction as in the hyperspectral model.

Table 3.2.Three models examined for estimation of bermudagrass CP from hyperspectral reflectance data consisting of individual wavelengths in wide spectral regions, eleven 10nm bands, and three variable width regional bands

	Individual Wavelengths in Regions	10 Nm Bands	Regional Bands
	440-509	440-449	440-509
	560-579	450-459	560-579
	700-719	460-469	700-719
		470-479	
		480-489	
		490-499	
		500-509	
		560-569	
		570-579	
		700-709	
		710-719	
VDV	73%	79%	68%

Table 3.3. Parameter Coefficients for spectral bands and conversion equation to be applied post coefficient calculation for estimation of bermudagrass CP from hyperspectral reflectance data.

Band (nm)	Coefficient	Conversion Equation
440-449	4.38	$y = 0.0362x^2 + 2.4544x + 45.749$
450-459	2.92	x=Sum (Coefficient*Spectral
460-469	1.56	Value)
470-479	0.53	
480-489	-0.02	
490-499	-0.34	
500-509	-0.61	
560-569	-1.17	
570-579	-1.64	
700-709	-1.57	
710-719	0.46	

Table 3.4.Model equations for prediction of CP from sensor data collected from a mobile platform for bermudagrass, wheat and tall fescue to be applied to validation data with seasonal influence where noted.

Species	Full Season	Early Season (Feekes 1-7)	Late Season (Feekes 7-10)
Bermudagrass	$30.68(NDVI^4)+0.25(\text{Laser Canopy Height}_{cm})+3.13$		
Wheat	$100-((11.63*NDVI^3)+(0.5*\text{Laser Canopy Height}_{cm})+(50+IRVI2)+16)$		
Tall Fescue		$104(NDVI^4)+7.33$	$16.5(NDVI^4)+12$

VIP scores for the laser canopy height, IRVI, and NDVI were examined for model construction inclusion. Three instances of hardware failure and two instances of sampling error reduced the total number of observations for the bermudagrass experiment to 266 observations. This resulted in a modeling data set of 218 and a validation set of 48 samples. Additionally, due to sampling error and GPS failure, 176 total samples were retained for the tall fescue analysis contributing 63 to the validation data and 114 to model construction. Data for the wheat model consisted of 389 samples for model construction and 107 for validation, with four omissions due to laser sensor malfunction. All conversion and modeling equations for experiments in which data were collected from the mobile platform are included in Table 3.4.

IV. Findings

Hyperspectral Model-Bermudagrass

CP concentrations from 74.7 (7.5%) to 168 (16.8%) g CP kg-1 were reported from the laboratory NIR analysis. This provided sufficient range to detect relationships between spectral data and CP concentrations. Spectral data was collected for a region between 340nm and 1030nm. All spectral data with negative relative irradiance values were eliminated from the subsequent analyses. This reduced the effective spectral region examined to 440nm to 910nm. The VP scores further reduced the data to 110 individual wavelengths with regions from 440nm to 509nm, 560nm to 580nm, and 700nm to 719nm. Of the three Models which were constructed using these spectra, the 10nm band model produced the highest VDV at 79%. The individual wavelength model produced a VDV of 73% and the wide band model produced a VDV of 68% (Table 3.2). As a result the 10 nm band model was

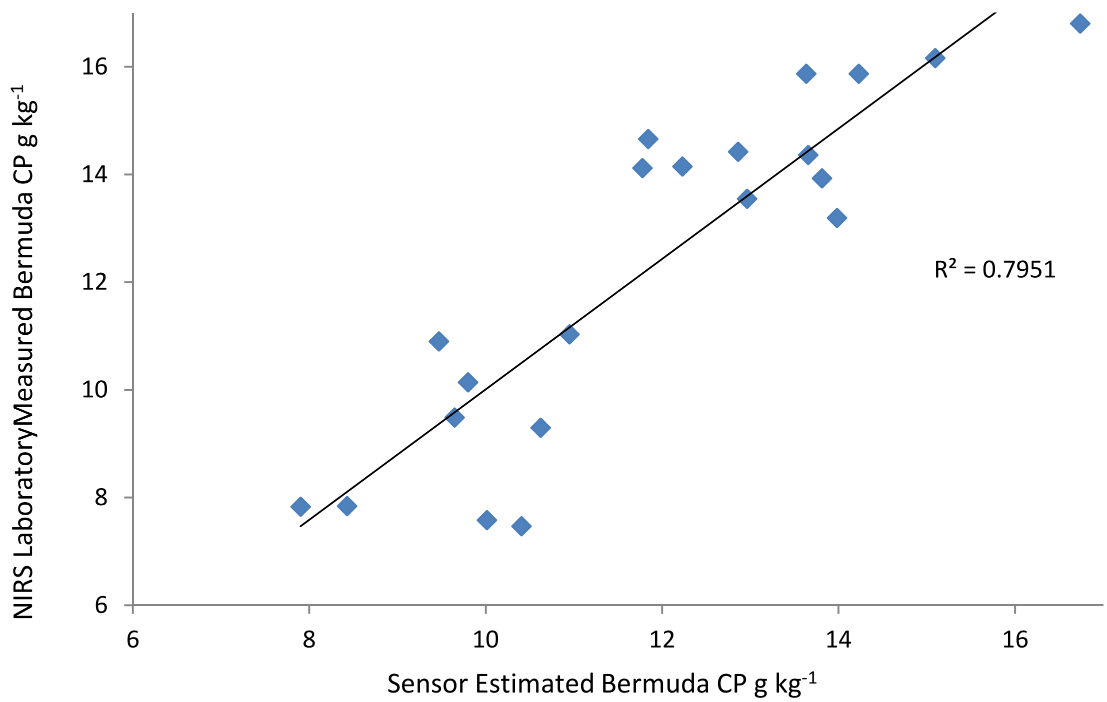

Figure 3.2. Bermudagrass CP Estimates produced from a hyperspectral reflectance model regressed with CP measurements from laboratory analyzed samples.

examined for predictive accuracy. Using the combination of the parameter estimates output from PROC PLS and the conversion equation, the measured to estimated CP for the validation data produced and R^2 of 0.80 with an intercept of 3.82 (Figure 3.2). Additionally, 10.5% MPE was observed for estimates as compared to measured CP (Table 3.5).

Active Spectral and Canopy Height Based CP Estimation Model-Bermudagrass

CP concentrations ranged from 43 (4.3%) to 230 (23%) g CP kg-1 for bermudagrass as reported from NIRS laboratory analysis. Although the PROC MIXED analysis revealed no significant difference in the relationship of CP to NDVI as compared to square, cubed or quartic function of NDVI, the quartic

Table 3.5.Laboratory measured CP and estimated CP from hyperspectral data collected on bermudagrass, as well as the by sample and Mean Percent Error (MPE) for validation data.

	Sample	CP% (NIR)	CP% Estimate	% Error
	NS1011	7.58	10.01	0.32
	NS1021	10.14	9.8	0.03
	NS1031	14.15	12.2	0.13
	NS1041	14.66	11.84	0.19
	NS1053	13.55	12.96	0.04
	NS1063	7.47	10.4	0.39
	NS1073	11.03	10.94	0.01
	NS2021	7.84	8.42	0.07
	NS2031	15.87	13.63	0.14
	NS2034	15.87	14.22	0.10
	NS2043	9.30	10.62	0.14
	NS2053	13.19	13.98	0.05
	NS2062	16.16	15.09	0.06
	NS2072	10.90	9.47	0.13
	NS3011	14.42	12.86	0.10
	NS3023	9.49	9.46	0.01
	NS3032	16.80	16.73	0.00
	NS3043	7.83	7.9	0.01
	NS3052	14.12	11.77	0.16
	NS3063	13.93	13.81	0.01
	NS4011	14.36	13.65	0.04
MPE				10.51

NDVI based CP estimation model did though produced the highest VDV for CP (74.8%) in combination with laser canopy height estimates (Table 3.6). The only parameter selected for model construction inclusion was NDVI due to the fact the VIP scores for both laser estimated canopy height and IRVI both fell below the 0.8 threshold for inclusion (SAS, 2012). The MPE for NDVI based CP estimation for bermudagrass was 11.66% (Table 3.6) and the linear regression relationship between the estimates and laboratory measured CP was characterized by an R^2 of 0.85 (Figure 3.3).

Active Spectral and Canopy Height Based CP Estimation Model-Tall Fescue

Tall fescue CP reported from NIRS laboratory analysis ranged from 60 (6.0%) to 300 (30%) g CP kg-^{1}. The PROC MIXED analysis for tall fescue indicated a seasonal interaction, which influenced the relationship between tall fescue CP and NDVI measurements (SEASON P=0.0182).

Table 3.6. Explanation of Variation in Dependent Variables (VDV) and Mean Percent Error (MPE) for CP estimation models from active spectral measurements and laser canopy height measurements for bermudagrass, wheat and tall fescue. Early Season (E: Feekes 1-7), Late Season (L:Feekes 7-10).

Species/Model	VDV	MPE
Bermuda	74.8%	12%
$Wheat_E$	71%	9%
$Wheat_L$	71%	23%
Tall Fescue $_E$	68%	16%
Tall Fescue $_L$	17%	19%

Due to this interaction the tall fescue CP was examined by season and across seasons. NDVI was the only parameter selected for model construction inclusion due to the fact the VIP scores for both laser estimated canopy height and IRVI both fell below the 0.8 threshold for inclusion (SAS, 2012). Estimates regressed with laboratory CP analysis were observed as exhibiting an R^2 of 0.63 across all seasons (Figure 3.4), 0.4104 (Figure 3.5) for fall and winter collected samples and 0.83 (Figure 3.6) for spring and early summer collected samples. The seasonal model for spring CP estimation (63 model construction samples and 26 validation samples) from NDVI measurements offered a VDV of 68% and MPE of 16% whereas that for fall (54 model construction samples and 33 validation samples) offered a VDV of only 17% and MPE of 19% (Table 3.6). This seasonal influence could likely be attributed to slow growing fall and winter forage with high CP concentrations though little photosynthetically viable biomass was present. While in contrast a higher volume of biomass was produced in the spring growing season and provided a much more homogenous target for spectral reflectance measurements.

Active Spectral and Canopy Height Based CP Estimation Model-Wheat

Laboratory NIRS analysis reported a CP range for wheat of 135 (13.5%) to 390 (39.0%) g CP kg-1. The PROC MIXED analysis indicated no significance in interaction among seasonally categorized CP measurements, laser estimated canopy height, NDVI, or IRVI. The VIP score for all sensor measurements were above the inclusionary threshold of 0.8 (SAS, 2012). Subsequently all were selected for model inclusion with the highest VDV for NDVI occurring in association with the cubed function, the squared function for IRVI, and the untransformed function for laser canopy height (71%) (Table 3.6). The R^2 for estimates as regressed to laboratory analyzed CP for the entirety of the validation data was 0.2725 (Figure 3.7) with an MPE of 14% (Table 3.6). In an effort to better understand this relationship the data was split into two sets: 1. data collected from 30 days after planting to the beginning of spring flush (November 2014 to February 2015: Feekes 1-7), and 2. data collected after the commencement of rapid spring growth (February 2015 to March 2015: Feekes 7-10). The regression relationship for senor based estimates to laboratory analyzed CP for the early season wheat was characterized by an R^2 of 0.65 (Figure 3.8) with an MPE of 9% whereas the later season wheat relationship exhibited an R^2 of 0.01 (Figure 3.9) with an MPE of 23% (Table 3.6). Some explanation of this can be offered in considering the potential CP variability which may occur due to mobilization of nitrogen in the wheat plant as morphological changes occur toward reproductive development in the spring.

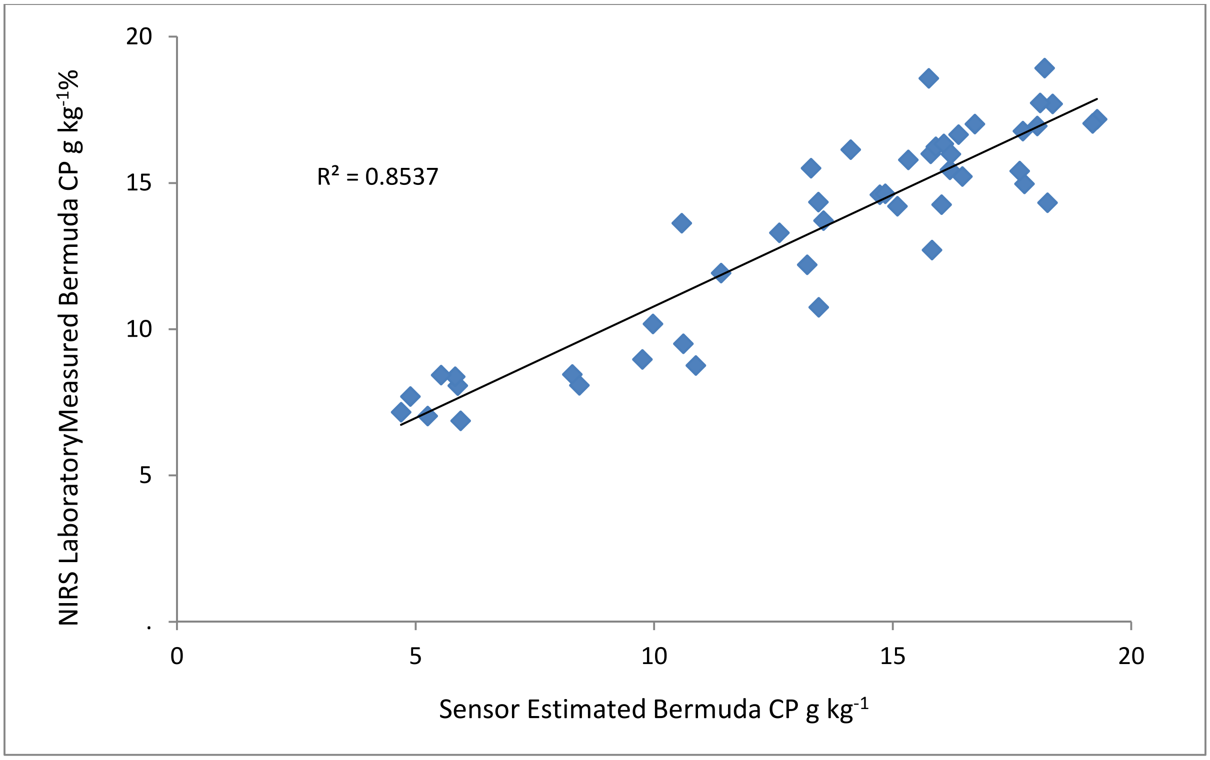

Figure 3.3. Bermudgrass CP estimates from active spectral sensor and laser canopy height model regressed with laboratory analyzed CP for the same samples to examine the agreement of predicted values with measured values.

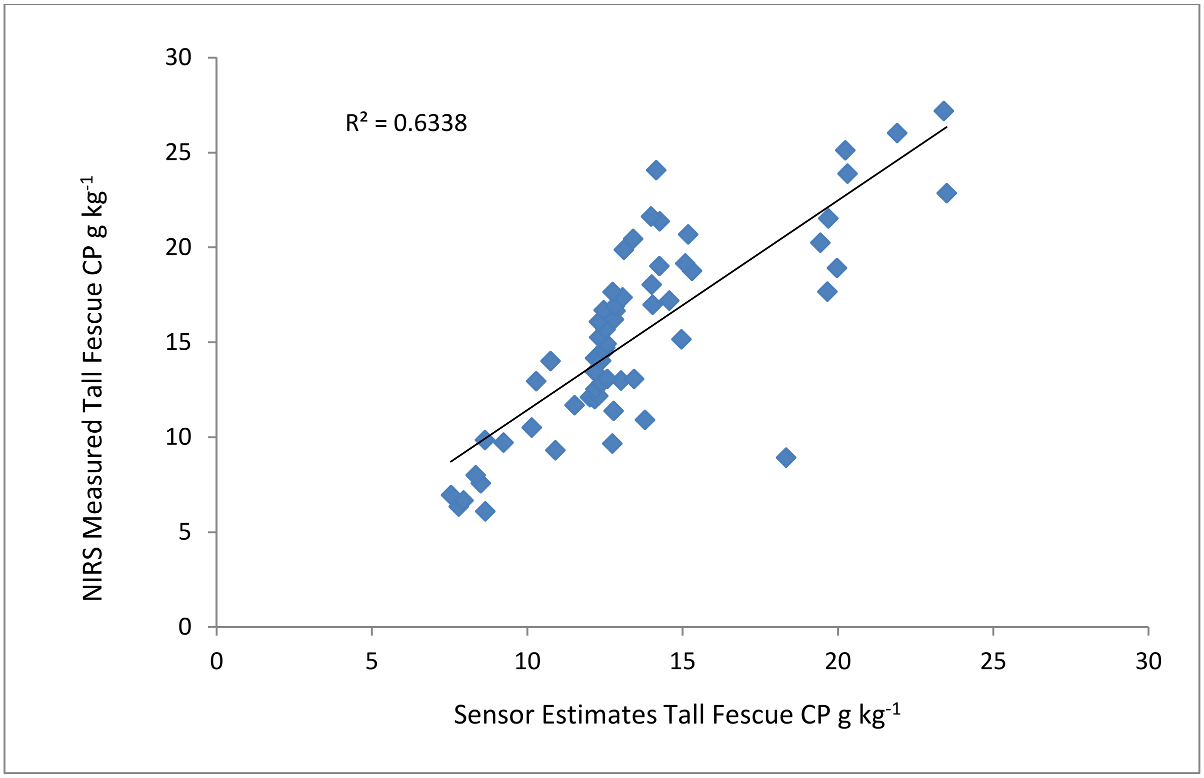

Figure 3.4. Tall fescue CP estimates from an active spectral sensor model regressed with laboratory analyzed CP for early and full season forage growth for the same samples to examine the agreement of predicted values with measured values.

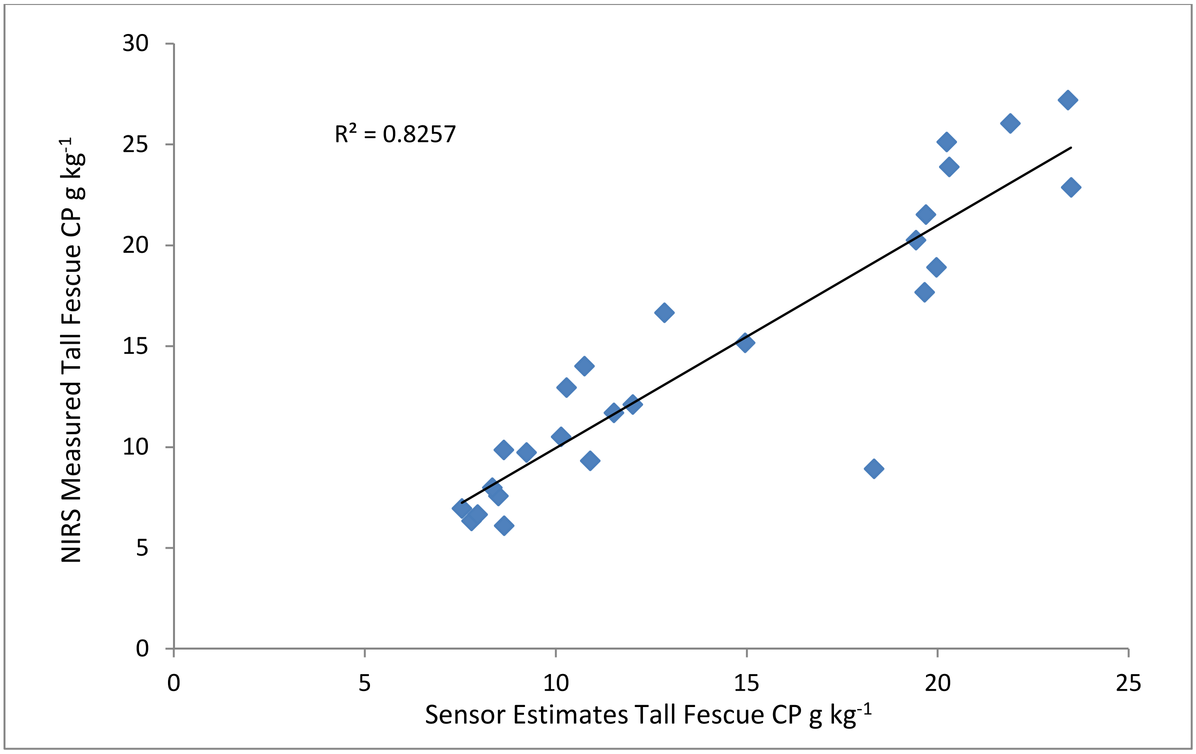

Figure 3.5. Tall fescue CP estimates from an active spectral sensor model regressed with laboratory analyzed CP for fall and winter forage growth for the same samples to examine the agreement of predicted values with measured values.

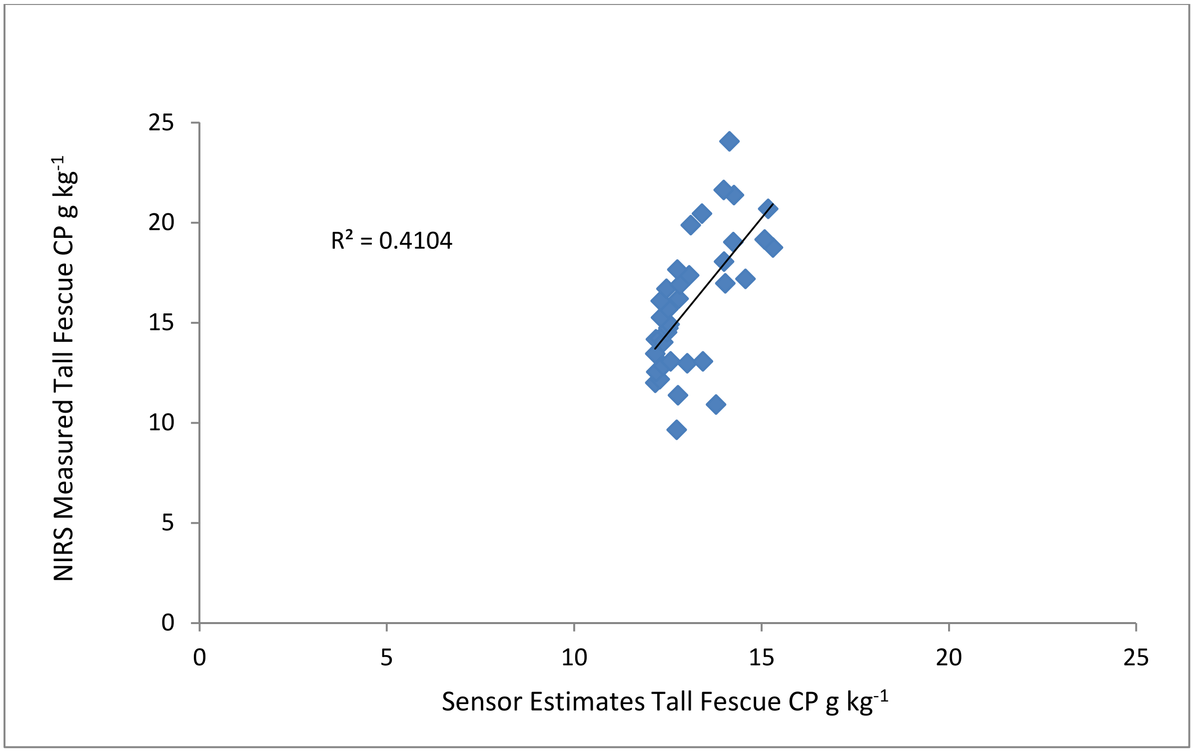

Figure 3.6. Tall fescue CP estimates from an active spectral sensor model regressed with laboratory analyzed CP for spring and early summer forage growth for the same samples to examine the agreement of predicted values with measured values.

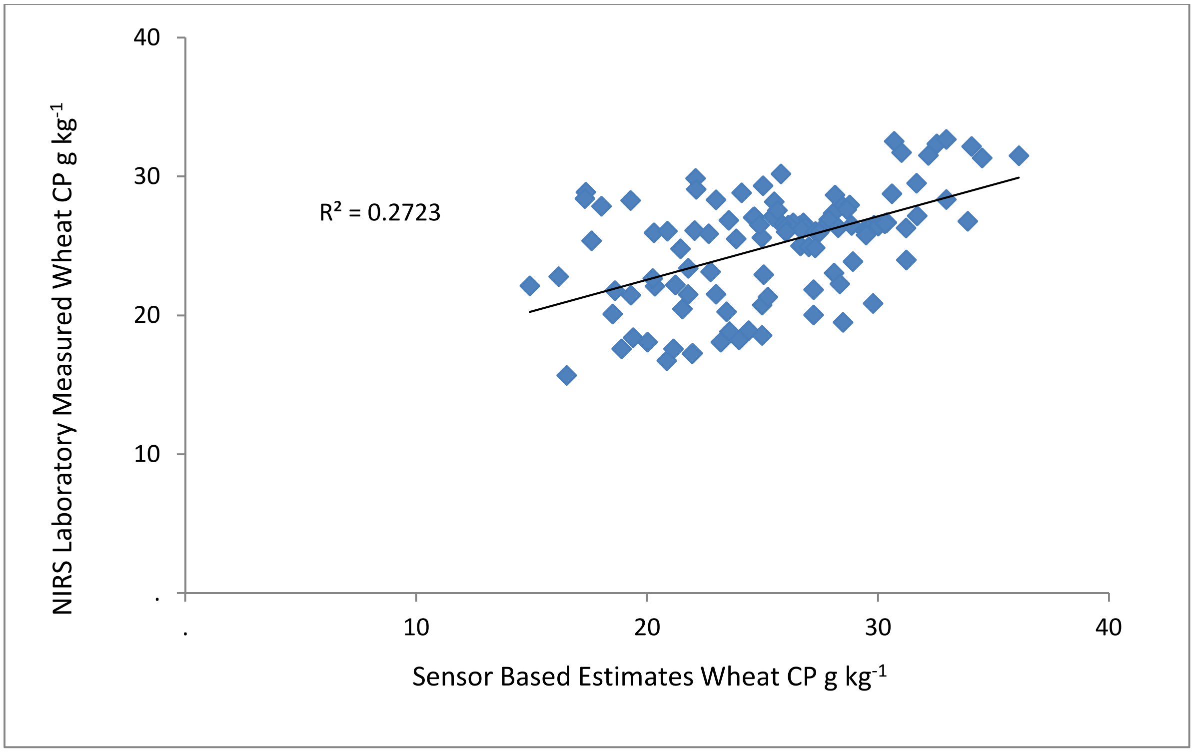

Figure 3.7. Wheat CP estimates from an active spectral sensor model regressed with laboratory analyzed CP for full season for the same samples to examine the agreement of predicted values with measured values.

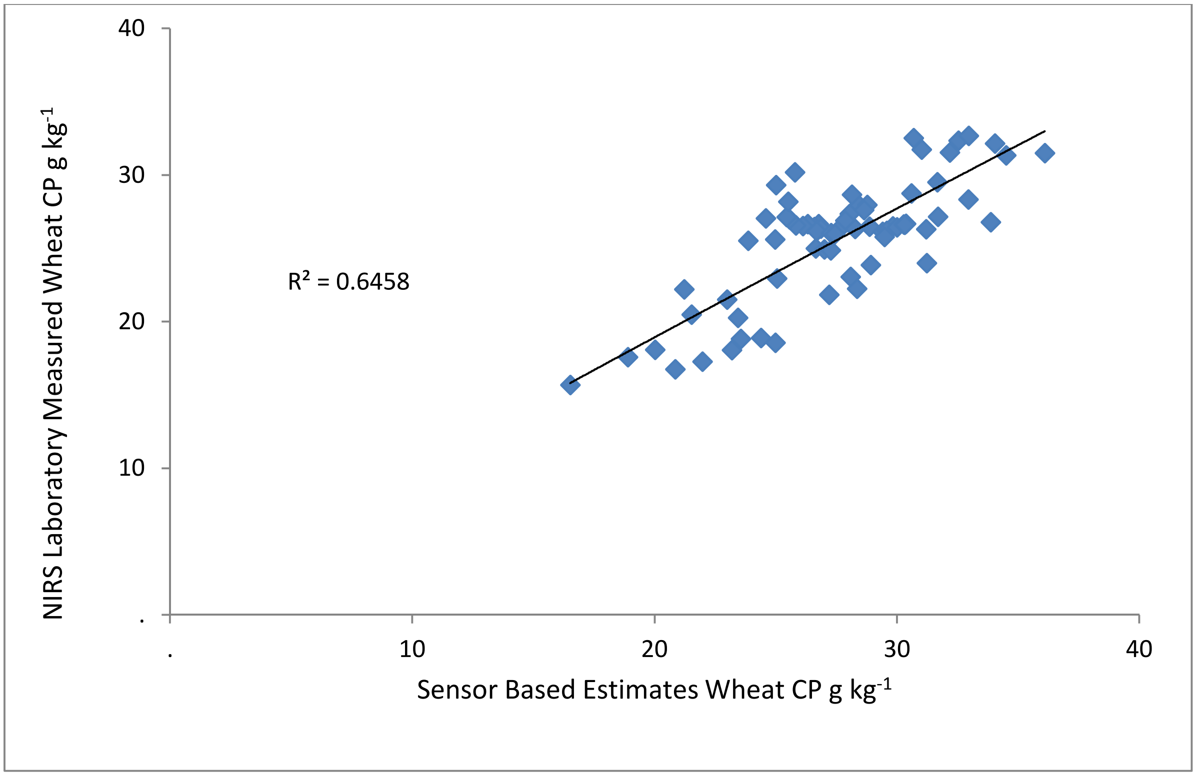

Figure 3.8. Wheat CP estimates from an active spectral sensor model regressed with laboratory analyzed CP for fall forage production for the same samples to examine the agreement of predicted values with measured values.

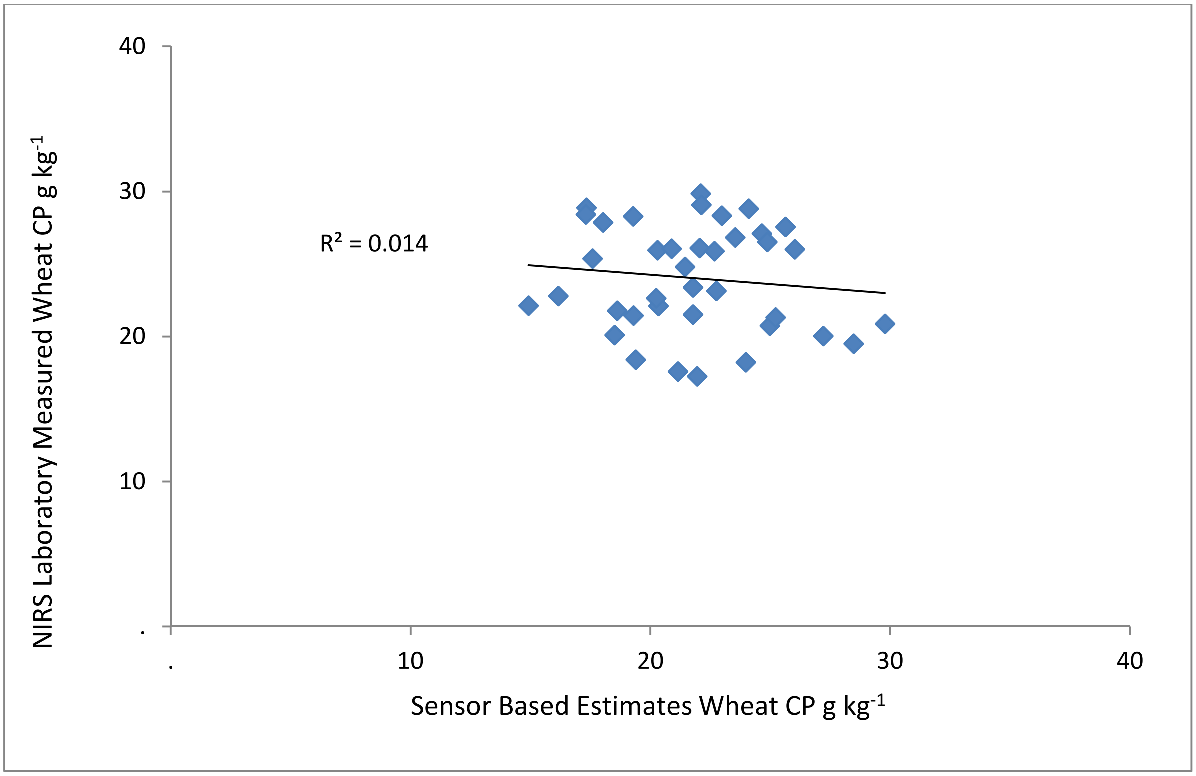

Figure 3.9. Wheat CP estimates from an active spectral sensor model regressed with laboratory analyzed CP for winter and spring forage production for the same samples to examine the agreement of predicted values with measured values

V. Conclusion

Sensor based estimates of CP in forage can be achieved with acceptable accuracy as compared to NIRS laboratory analysis for bermudagrass, tall fescue in spring and early summer and to some degree wheat prior to spring flush. Though year-round sensor based estimates of CP would be optimal, confounding factors such as morphological development of annual forages and limited production of photosynthetically viable tissue by perennial forages in some growing seasons may limit this possibility. The research reported here though does indicate that active spectral

instrumentation and in some cases combined with canopy height sensing equipment can produce estimates comparable to those produced using hyperspectral instrumentation. This is an important issue to examine as most hyperspectral instruments cannot be used from a mobile platform in an on-the-go system where a continuous a stream of data is acquired as the system is moved across an area of interest. The ability to utilize sensing equipment in this on-the-go manner allows for data to be collected much more quickly over a greater area in substantially less time than would be necessary for the point type data collection associated with most hyperspectral instruments.

In order to improve the accuracy with which CP can be modeled, further investigation using active spectral instrumentation that can obtain reflectance measurements for additional spectral bands or wavelengths could be contributive. Additionally, examination of a variety of forage species for sensor based CP estimation may also offer some insight to additional areas of spectra which may be appropriate for model inclusion. The models used for estimation of CP will likely be dependent on species and may be dependent on seasonally as well.

The implications for decision making for stocking rates also should be considered as the data collected from a mobile platform such as used in this study, can provide estimates in substantially less time than would be expected for physical sample collection and laboratory sample submission. This type of system could also be useful for plant breeders in making cultivar selection for high quality forages without the time intensive data collection scenarios associated with sampling large collections of germplasm.

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