Real-Time Moisture Measurement on a Forage Harvester Using Near-Infrared Reflectance Spectroscopy

M. F. Digman, K. J. Shinners

Abstract. *A mobile, diode-array NIR spectrometer was integrated into the spout of a self-propelled forage harvester to measure crop moisture. Spectra and moisture reference samples were collected in 2004 and 2005 for the development of laboratory and field-based moisture calibrations. Moisture prediction models for whole-plant corn silage (WPCS) developed using laboratory data had a root mean standard error of cross-validation (RMSECV) of 1.1% using five principle components (PCs), while a calibration developed using field data had an RMSECV of 3.3% using four PCs. Alfalfa validation results produced RMSECVs of 2.5% using four PCs and 3.7% using three PCs for models using laboratory and field data, respectively. Field data were predicted with calibrations developed using laboratory data with similar error levels, but more spectral information was required. A laboratory-based alfalfa model predicted field data with a root mean standard error of prediction (RMSEP) of 3.4% using three PCs as compared to the field model's RMSECV of 3.7% using three PCs. Similar trends were found with WPCS models. Predicting data independent of type of crop resulted in the utilization of more PCs but with higher RMSEPs than the cross-validation results of the predicted dataset. The sensor and associated calibrations were able to predict forage moisture adequately, although more diverse data and further calibration development are needed to improve sensor accuracy to the desired range of ±2.0 percentage units.*

Keywords. *Forage, Mobile NIRS, Moisture, NIR, NIRS, On-harvester NIRS, Precision agriculture.*

Ensiling forage allows producers to provide a season-independent feedstuff of consistent quality. The success of ensiling is due to the development of an anaerobic environment that promotes fermentation. Fermentation depends on many factors, including crop moisture, pH, presence of certain microorganisms, and available fermentable sugars (Barnes et al., 2003).

Water content is a major factor influencing successful fermentation. Thus, the focus of this research was to aid the forage producer in the prediction of crop moisture. Moisture prediction will guide decisions regarding harvest and storage of forage crops, minimizing production costs and maximizing forage quality. Management decisions influenced by moisture level may include determining optimum harvest time, determining targeted use of silage, storage method, and optimizing harvester setup and site-specific crop management (Kormann and Tillmann, 2004).

In the early 1970s, USDA research scientist Karl Norris identified the capabilities of near-infrared reflectance spectroscopy (NIRS) and developed statistical methods to identify constituents in agricultural products (Fahey et al., 1994). Presently, NIRS is used to determine the quality of agricultural products through prediction of concentration of desired constituents. These analyses are conducted in laboratories around the world linked together with calibration networks.

The technology under investigation here owes its success to the same physical and chemical theory that enables laboratories to provide accurate constituent information of agricultural products. Until recently, the measurements made by an NIR spectrometer were sensitive to environmental and physical factors, including sample presentation, temperature, and humidity. Advancements in NIRS hardware and statistical methods afford a more robust NIRS model. These new robust models lend themselves to successful integration into mobile applications (Paul, 2003), which will result in both moisture and constituent information in real-time, offered in a way that may be addressed spatially for integration into modern, site-specific farming methods.

A patented system for an on-harvester NIRS has been presented (Wright et al., 2002). This patent describes a rugged system for on-harvester analysis of grain and presents the challenges faced for calibration of an on-line system, specifically the inherent variability associated with scanning undried and un-ground samples.

In 2003, Welle et al. (2003) published results measuring forage parameters on a plot harvester. In 1998 and 1999, Welle and his associates collected 281 samples to develop on-harvester NIRS calibrations for dry matter, starch, in vitro digestibility, and soluble sugars. Their calibrations yielded standard errors of cross-validation (SECVs) of 1.18% for DM, 2.36% for starch, 1.92% for in vitro digestibility, and 1.38% for soluble sugars.

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Recently, many have investigated NIRS for optimizing cultivar selection in forage breeding programs (Féménias, 2004; Welle, 2004; Reyens, 2004; Sinnaeve et al., 2004; Dardenne and Féménias, 2004; Van Waes et al., 2004). NIRS was used to predict dry matter, crude protein, crude fiber, neutral detergent fiber, acid detergent fiber, soluble sugar, and organic matter digestibility. On-harvester prediction performance was always lower than the standard laboratory NIRS analysis, with many researchers using the standard NIRS analysis as their reference method.

Measuring forage parameters on a plot harvester is quite different than that on a commercial forage harvester. Many plot harvesters allow for subsampling of the forage stream, where the subsampled forage is allowed to pass by the spectrometer in a static column or on a slow-moving conveyor belt. This technique would not be feasible on a commercial forage harvester, as the crop mass-flow rate is many times greater than that of a plot harvester. Therefore, the spectrometer must be able to make rapid measurements of the passing forage. In 2002, Kormann and Flohr (2002) evaluated three NIR spectrometers for measurement of forage properties on a forage harvester. Their research found that moisture, protein, and starch could be predicted with SECVs of 1.39%, 0.28%, and 1.62%, respectively.

The research reported here investigates NIRS technology as a means to meet the challenge of predicting forage moisture in real time on a commercial harvester. The feasibility of this technology was investigated through calibration development and verification. The goal was to develop a moisture calibration that will be insensitive to the variability expected in mobile forage harvesting.

Materials and Methods

Spectra and moisture reference samples were collected throughout the harvest season in 2004 and 2005 at various field locations at the University of Wisconsin Arlington Agricultural Research Station, Marshfield Agricultural Research Station, USDA Dairy Forage Research Center Farm, and several dairies in southwest Wisconsin and central California for the development of laboratory and field-based moisture calibrations. Laboratory data were either collected in conjunction with on-harvester (field) data or from samples taken from the harvesting crew's trucks or wagons.

Materials

Laboratory-based spectral data were collected with two spectrometers during the 2004 season. A third sensor was added for the 2005 harvest season. The first spectrometer was a Zeiss Corona 45 NIR (Carl Zeiss; Jena, Germany). The Corona 45 (C45) is an indium gallium arsenide (InGaAs) diode array spectrometer commercially available from Zeiss. The Corona 45's diode array consists of 128 diodes with a wavelength range of 950 to 1680 nm at an interpolated resolution of 6 nm. The Corona 45 employs Zeiss's OMK measuring technology, in which 15 optical fibers are evenly arranged in a circle. This system provides a large measuring area of 20 mm diameter that is insensitive to variations in sample distance.

The second spectrometer resulted from an effort to develop a more cost-effective, robust sensor to meet the demands of moisture measurement on the harvester. The 2004 prototype, CP04 (Carl Zeiss; Jena, Germany), featured a 256 diode InGaAs array with an interpolated wavelength range of 950 to 1530 nm and an interpolated resolution of 2 nm. To reduce cost and improve robustness, diode array cooling and fiber optic light detectors were not features of this spectrometer.

In 2005, a third spectrometer was added to the sensor array. The 2005 prototype sensor, CP05 (Carl Zeiss; Jena, Germany), differed from the CP04 with the following features: automatic internal referencing, and integration of the harvesting lens. Internal space constraints resulting from the hardware necessary for the sensor's new features required that the angle of illumination and light detection be altered from the 2005 sensor. However, the relationship between the angle of illumination and light detection was maintained.

To ensure a consistent optical path length during laboratory data collection, a Zeiss Turnstep was used to position the sample over the spectrometer. The Turnstep also provided a means of rotating the sample at 60 rpm to allow a greater area to be observed. Sample density was not recorded, as work conducted throughout the 2004 harvest season indicated no influence of sample density on a given calibration's ability to predict moisture.

A self-propelled forage harvester (model 7800, John Deere, Zweibrücken, Germany) was used for collection of field data. The harvester was equipped with a windrow pickup (model 645, John Deere, d'Arc-les-Gray, France) for haylage and a row-sensitive corn head (model 666R, John Deere, Zweibrücken, Germany) for whole-plant corn silage (WPCS). In WPCS, the harvester was also fitted with a crop processor. The harvester's spout was fitted with the CP04 and CP05 prototype sensors for collection of field spectra during the 2004 and 2005 harvest seasons, respectively. The sensor location was just above the crop accelerator, where the crop stream transitions from nearly vertical to horizontal (fig. 1).

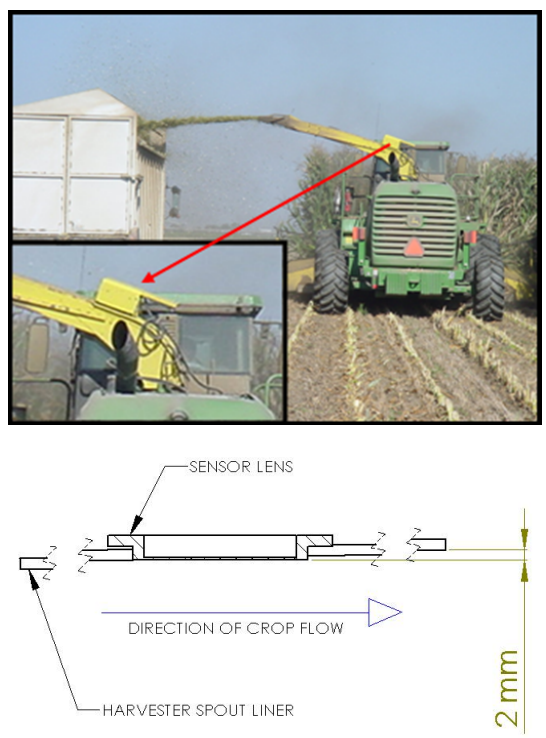

Figure 1. (top) NIRS sensor mounted on forage harvester spout; (bottom) cross-section of sensor located on harvester spout.

This location was chosen because it was believed that intimate lens-to-crop contact would be ensured. The sensor's view of the crop was through a sapphire lens that penetrated the spout through a 50 mm diameter hole. Sapphire was chosen for its wear resistance properties as compared to silica glass. Lens wear is a concern due to the high-speed crop stream containing soil and other abrasive contaminates.

Methods

Field reference spectra were collected after ensuring that the harvester had reached equilibrium, as determined by a uniform crop stream from the spout; five spectra were collected in 1 s intervals. The harvesting was then immediately halted. To determine moisture content, one sample was collected after each run. This sample consisted of no less than ten subsamples totaling approximately 2 kg. Samples were collected in plastic bags to prevent moisture loss. Approximately five runs were completed before emptying the wagon. After the wagon had been emptied, the lens was checked for crop residue and cleaned if necessary. At this time, the five samples were placed in the refrigerator where they were held for no more than 8 h. Laboratory spectral analysis and moisture reference subsampling were performed after completion of the day's harvest.

Samples, either collected from freshly harvested material or removed from refrigeration, were scanned in the laboratory. If refrigerated, the sample was allowed to reach ambient temperature. Then, mixing by hand to homogenize, ensuring that the sample would be representative, a subsample was taken. The subsample was placed in a 179 mm diameter × 90 mm deep glass bowl, which accommodated a sample size of approximately 300 g, depending on sample moisture. The subsample was then placed on the first spectrometer, the Turnstep was activated, and five spectra were collected in 1 s intervals. The subsample was then transferred to the second and third spectrometers and scanned utilizing the same method. The subsample was emptied into a container for mixing before it was returned to the glass bowl for subsequent scans. Each subsample was scanned five times in this manner. These scans were later averaged to be compared with reference moisture. Glass bowls were cleaned after every fifth use or more frequently if crop conditions left excess residue.

The 300 g subsample was then split between two preweighed paper bags. Each bagged sub-subsample was weighed and then transferred to a forced-air drying oven where the temperature and drying time were 103°C and 24 h, respectively, per ASABE Standard S358.2 (*ASAE Standards*, 2003).

Two methods of outlier detection were employed to remove erroneous spectra from the calibration dataset. The first used a comparison of the two reference moisture values. Spectra were associated with two replicate subsamples for determination of reference moisture. If the difference between replicate reference moistures was greater than two moisture percentage units, the sample and its spectra were rejected. Less than 5% of the samples varied more than 1% moisture between replicates.

The second method of outlier rejection included visual inspection of light reflection spectra. Any spectra that appeared abnormal when compared to the whole dataset were rejected (fig. 2). Less than 5% of the spectra were abnormal or contained no reflectance information.

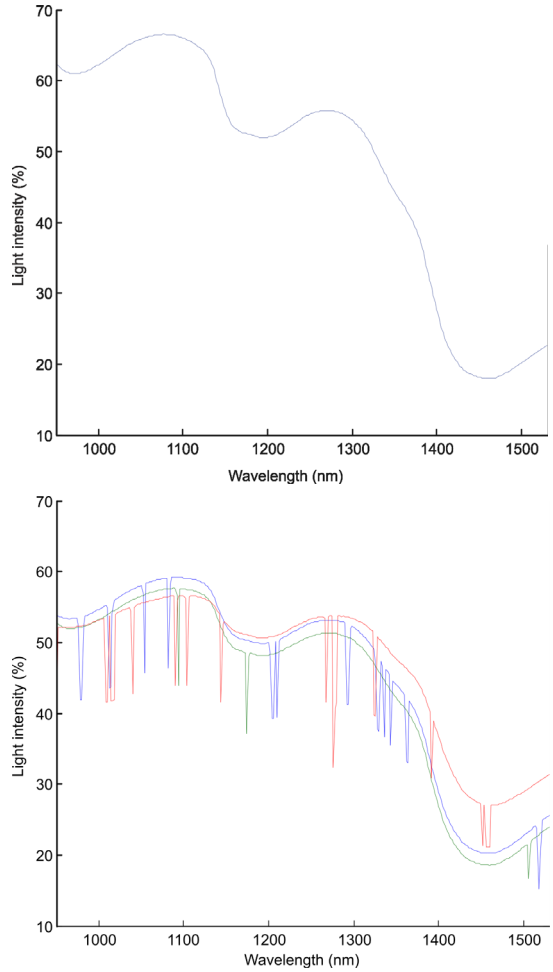

Figure 2. Near-infrared reflectance spectra plotted as light intensity (%, *y*-axis) as a function of wavelength (nm, *x*-axis) for (top) a normal spectrum and (bottom) abnormal spectra.

The spectra files were imported into Unscrambler (Unscrambler, 2005), a commercial multivariate analysis software package, in which math pre-treatment, data compression, and regression were performed. Data compression and regression were performed utilizing Unscrambler's partial least squares regression (PLSR) algorithm. Several math pre-treatment schemes were employed to assess not only each method, but also combinations thereof.

Math pre-treatments are transformations of the spectra used to remove non-constituent spectral information (Roberts et al., 2004). Math pre-treatments and combinations explored included no treatment, Savitzky-Golay (SG) first derivative (SG1), SG second derivative (SG2), multiplicative scatter correction (MSC), MSC + SG first derivative (MSC+SG1), MSC + SG second derivative (MSC+SG2), standard normal variate (SNV), SNV + SG first derivative (SNV+SG1), and SNV + SG second derivative (SNV+SG2) (Unscrambler, 2005). The derivative terms were determined across six wavelengths, including three left-side terms and three right-side terms employing a second-order polynomial. The choice of six wavelengths was based on interactions with the sensor manufacturer.

The models were compared with one another based on three performance criteria. Each calibration was ranked first by the optimal number of principal components (PCs) as

identified by Unscrambler. Unscrambler suggested the optimal number of PCs as the first local minimum in the residual variance plot, unless later PCs gave significantly lower residual variance. The fewer the number of optimal PCs, the less spectral information was required to build the calibration. A calibration with fewer PCs will exhibit more robustness when predicting future data, as it is less likely to be overfit to the data used during calibration development. The second criterion for calibration performance was root mean standard error of prediction (RMSEP) or cross-validation (RMSECV). The goal was to obtain an RMSEP of less than two moisture percentage units. The final comparison was the correlation coefficient (r). Calibrations with r closer to one indicated that there was good fit between the actual moisture and that predicted by the calibration. These last two performance criteria were the result of either predicting a dataset independent of the calibration data or of employing the cross-validation technique, which utilized random sets of ten samples (Unscrambler, 2005). These relationships can be depicted in a predicted versus actual concentration (moisture) plot.

Results and Discussion

Conventional Calibration Performance

The first results presented in this section include performance of conventional calibrations, i.e., calibrations that only contain data from one crop (alfalfa or WPCS) and one presentation method (laboratory or field). All calibrations presented in this section were verified using the cross-validation technique.

The WPCS dataset consisted of 200 spectra collected for both laboratory and field settings in Wisconsin during the 2004 harvest season. The 2005 data collection season in Wisconsin yielded 107 laboratory and field spectra; an additional 72 field spectra were collected in California. Laboratory and field data were collected in 2004 with the CP04 spectrometer, whereas data in 2005 were collected for both laboratory and field settings with the CP05 and only for laboratory settings with the CP04.

The cross-validation results for the WPCS laboratory models showed very low RMSECV values for all math pre-treatments investigated (table 1). Overall, performance was very similar for all math pre-treatment schemes. The low RMSECVs are thought to be the result of a very uniform set of calibration data with harvesting and crop conditions, which were similar not only throughout each year but also from year to year. Corona 45 results were slightly better than the prototype sensor, as evident in the lower number of PCs required.

Table 2. Calibration performance for moisture based on cross-validation using WPCS data[a] collected in the field for 2004 and 2005 using CP04 and CP05 sensors.

Dynamic WPCS Calibration		Performance	
Math Pre-treatment	PCs	RMSECV (MC % w.b.)	r
SG1	4	3.3	0.79
SG2	5	3.1	0.81
No treatment	5	3.2	0.80
SNV+SG2	7	2.9	0.84
MSC+SG2	7	2.9	0.84
SNV+SG1	7	3.0	0.83
MSC+SG1	8	2.8	0.85
MSC	9	2.8	0.86
SNV	10	2.8	0.85

[a] Field WPCS model reference moisture statistics: range = 44% to 80% w.b., mean = 63% w.b., and standard deviation = 7% w.b.

Field WPCS model performance (table 2) was lower than the laboratory performance (table 1). This is most likely the result of the larger variability associated with this dataset, as field spectra were collected throughout the day in variable ambient conditions. Material presentation to the sensor would have also been less controlled in the field case. Only two math pre-treatment models had the same number or fewer PCs than the calibration model with no math pre-treatments. The best pre-treatments all employed a derivative, or scatter correction and derivative combination. Scatter correction and derivative math pre-treatment combinations will show the highest performance throughout the comparisons to follow. The worst performance was seen when only scatter correction was employed.

One of the major differences between the WPCS laboratory and field datasets was the presence of the California data in the latter. Consequently, field calibrations were developed without the California data to determine the influence of these data on calibration performance. The California dataset added only 72 spectra to the calibration dataset, but it had an impact on both calibration and pre-treatment performance (table 3). The poor performance could be the result of many factors, including but not limited to climate, ambient conditions at the time of harvest, or physiological effects associated with development of an irrigated crop.

The alfalfa dataset consisted of 588 laboratory and 291 field spectra collected in the 2004 harvest season and 451 laboratory and 283 field spectra collected during 2005.

Table 1. Calibration performance for moisture based on cross-validation using WPCS data[a] collected in the laboratory for 2004 and 2005.

CP04 and CP05 Sensors		Performance		Corona 45 Sensor		Performance	
Math Pre-treatment	PCs	RMSECV (MC % w.b.)	r	Math Pre-treatment	PCs	RMSECV (MC % w.b.)	r
SNV+SG1	5	1.1	0.96	MSC+SG1	4	1.1	0.95
SNV+SG2	5	1.1	0.96	SG1	4	1.1	0.97
MSC+SG1	5	1.1	0.96	MSC+SG2	4	1.2	0.97
SNV	5	1.4	0.94	SNV+SG1	4	1.2	0.97
MSC+SG2	6	1.2	0.95	SNV	5	1.1	0.97
SG1	6	1.3	0.97	MSC	5	1.2	0.97
SG2	6	1.3	0.97	No treatment	5	1.2	0.97
MSC	7	1.1	0.98	SG2	6	1.1	0.95
No treatment	7	1.3	0.94	SNV+SG2	6	1.2	0.97

[a] Reference moisture statistics: range = 44% to 73% w.b., mean = 62% w.b., and standard deviation = 5% w.b.

Table 3. Calibration performance for moisture based on cross-validation using WPCS data[a] collected in the field for 2004 and 2005 using only Wisconsin data and CP04 and CP05 sensors.

Math Pre-treatment	PCs	Performance RMSECV (MC % w.b.)	r
MSC+SG2	2	3.1	0.80
SNV+SG2	2	3.1	0.80
MSC	3	3.1	0.81
MSC+SG1	4	3.0	0.82
SNV+SG1	4	3.0	0.82
SNV	4	3.0	0.81
SG2	4	3.1	0.81
No treatment	5	3.0	0.81
SG1	6	3.0	0.82

[a] Reference moisture statistics: range = 44% to 73% w.b., mean = 61% w.b., and standard deviation = 5% w.b.

Table 5. Calibration performance for moisture based on cross-validation using alfalfa data[a] collected in the field for 2004 and 2005.

Dynamic Alfalfa Calibration: Math Pre-treatment	PCs	Performance RMSECV (MC % w.b.)	r
SNV+SG1	3	3.7	0.91
MSC+SG1	3	3.8	0.91
SNV+SG2	3	3.9	0.90
MSC+SG2	3	3.9	0.90
SG1	4	3.5	0.92
SG2	4	3.6	0.92
SNV	7	3.2	0.93
No treatment	8	3.1	0.94
MSC	8	3.2	0.93

[a] Reference moisture statistics: range = 27% to 82% w.b., mean = 58% w.b., and standard deviation = 9% w.b.

Laboratory and field data were collected in 2004 with the CP04 spectrometer, whereas data in 2005 were collected for both laboratory and field settings with the CP05 and only for laboratory settings with the CP04. The 2004 dataset only included data from the Arlington research farm, while the 2005 dataset also included data from Marshfield and Prairie du Sac research farms and several locations in southwest Wisconsin.

The alfalfa laboratory calibration performance (table 4) was slightly worse than for the WPCS (table 1). The decreased performance is most likely the result of the larger variability associated with the alfalfa dataset. Alfalfa data were collected over a larger time period, at more locations with variable agronomic and ambient conditions, included more varieties, and included alfalfa-grass mixtures. Math pre-treatments were successful in both reducing the number of optimal PCs and RMSECVs in laboratory-based alfalfa calibrations. The Corona 45 calibration models outperformed the prototype sensors, as evident in the lower number of PCs and lower RMSECVs. It is hypothesized that the poorer performance of the prototype sensor could be the consequence of the absence of diode array cooling and OMK measuring optics.

The calibrations developed with alfalfa spectra collected in the field were not as effective at predicting moisture as those developed with data collected in the laboratory (table 5). Math pre-treatments were successful in both reducing the number of optimal PCs and RMSECVs in field alfalfa data in all cases. Poor performance was seen in calibrations not utilizing the derivative pre-treatment, as evident in the large number of optimal PCs associated with the MSC, SNV, and no-treatment models.

Predicted vs. actual moisture content plots were generated for the best performing calibrations (fig. 3). Comparing the top two plots to the bottom reveals a loss in prediction accuracy associated with field data collection that is independent of crop. Comparing the left two plots to the right illustrates the larger variability in moisture content associated with the alfalfa dataset.

Predicting Moisture Independent of Presentation

Predicting moisture independent of sample presentation is of great interest when considering the future direction of this research. Specifically, predicting field data with a laboratory model would greatly reduce the overhead associated with collecting field calibration data. It would also increase the mobility of the data collection effort, as the harvester would not need to be moved to acquire data in additional regions. The purpose of the following comparisons was to quantify the ability of a calibration developed with laboratory data to predict data collected in the field and to identify which math pre-treatment schemes were most successful in removing the influence that field data collection had on the spectra.

The first comparison in this section included predicting alfalfa field data with laboratory data (table 6). When predicting field data with a laboratory calibration model, it was evident that the laboratory models had similar to worse performance, as indicated by the number of optimal PCs and magnitude of the RMSEPs. Math-pretreatment performance

Table 4. Calibration performance for moisture based on cross-validation using Wisconsin alfalfa data[a] collected in the laboratory for 2004 and 2005.

CP04 and CP05 Sensors: Math Pre-treatment	PCs	Performance RMSECV (MC % w.b.)	r	Corona 45 Sensor: Math Pre-treatment	PCs	Performance RMSECV (MC % w.b.)	r
SNV+SG2	4	2.5	0.97	MSC+SG2	4	2.2	0.95
MSC+SG2	4	2.5	0.97	MSC+SG1	5	1.6	0.97
SNV+SG1	4	2.7	0.96	SNV+SG1	5	1.7	0.97
MSC+SG1	5	2.5	0.97	SG1	5	1.9	0.98
SG2	6	2.6	0.97	No treatment	5	2.0	0.98
MSC	6	2.7	0.96	SNV	5	2.1	0.96
SNV	6	2.7	0.96	SNV+SG2	5	2.2	0.97
SG1	6	2.9	0.96	MSC	6	1.9	0.98
No treatment	6	3.1	0.95	SG2	6	2.1	0.98

[a] Reference moisture statistics: range = 18% to 82% w.b., mean = 57% w.b., and standard deviation = 10% w.b.

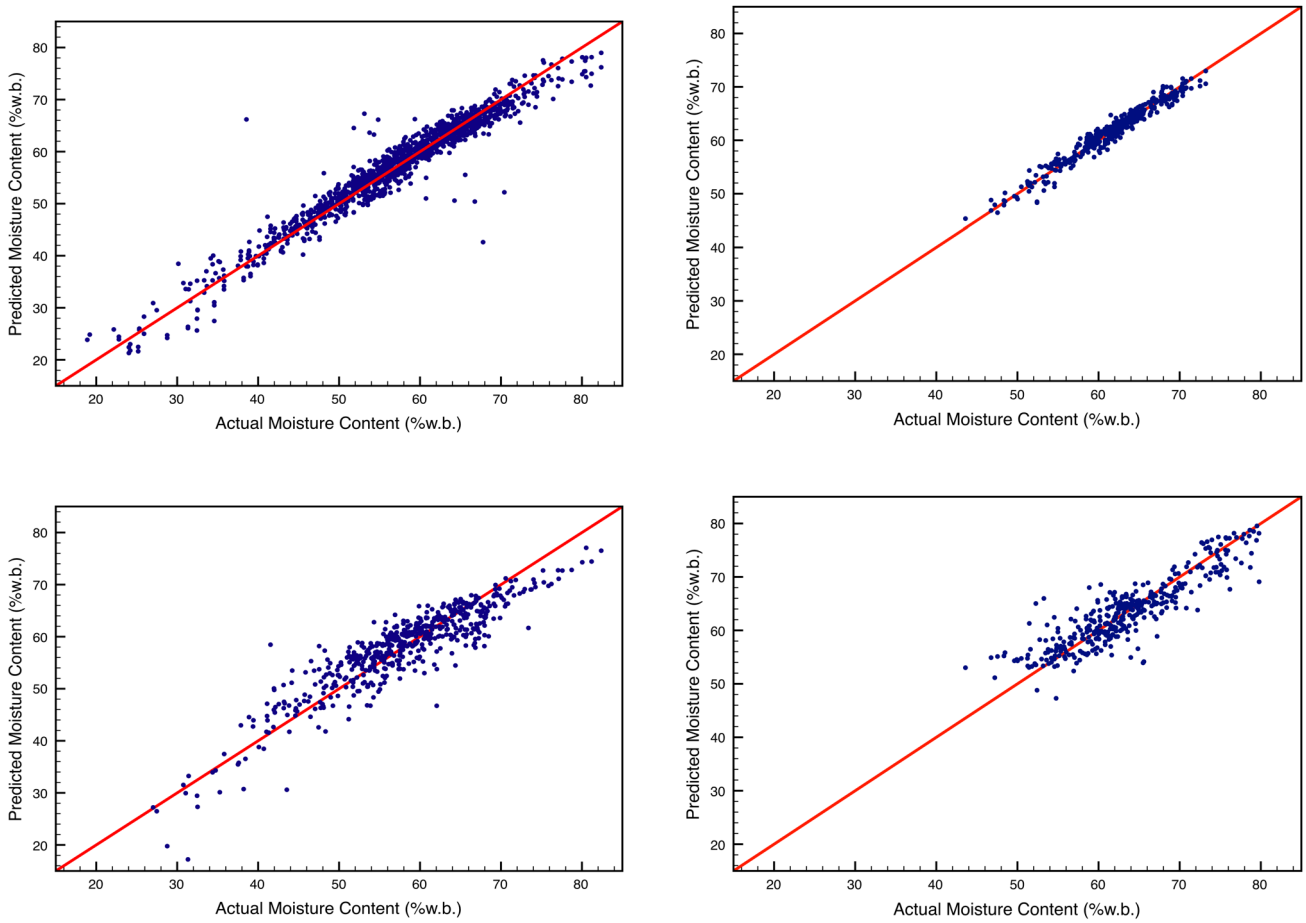

Figure 3. Calibration performance depicted as predicted vs. actual moisture content (% w.b.) for best performing models including alfalfa laboratory (SNV+SG2, top left), whole-plant corn silage laboratory (SNV+SG1, top right), alfalfa field (SNV+SG1, bottom left), and whole-plant corn silage field (SG1, bottom right).

was similar for each model, leading one to speculate that math pre-treatments do not have the ability to remove the added variance or noise in the data collected in the field, but performance is more strongly associated with some other source of variability.

The second comparison included predicting WPCS field data with a calibration developed with laboratory data (table 7). The California data were removed from the field dataset because they did not contain laboratory data. When predicting field data, it is evident that laboratory models had similar to worse performance, as evident in the number of optimal PCs and the magnitude of the RMSEPs. Calibrations employing both derivative and scatter correction pre-treatments proved to have the best performance. This result is similar to that seen in other comparisons.

The previous comparisons included calibrations developed where the samples that were scanned in the laboratory were collected at the same time as those where field scans were made. The following comparisons were designed to investigate the robustness of a laboratory calibration given an independent field dataset. Developing the laboratory calibration with data collected in 2005 and utilizing this calibration

Table 6. Alfalfa laboratory (2004 and 2005) calibration performance for moisture predicting alfalfa field data set (2004 and 2005) compared to an alfalfa field (2004 and 2005) calibration validated using cross-validation technique.

Laboratory-Based Alfalfa Model		Performance Predicting Field Data		Field Alfalfa Model		Cross-Validation Performance	
Math Pre-treatment	PCs	RMSEP (MC % w.b.)	r	Math Pre-treatment	PCs	RMSECV (MC % w.b.)	r
SNV+SG2	4	3.4	0.93	SNV+SG1	3	3.7	0.91
MSC+SG2	4	3.5	0.92	MSC+SG1	3	3.8	0.91
SNV+SG1	4	4.7	0.88	SNV+SG2	3	3.9	0.90
MSC+SG1	5	5.0	0.88	MSC+SG2	3	3.9	0.90
SG1	6	4.3	0.90	SG1	4	3.5	0.92
SG2	6	4.3	0.90	SG2	4	3.6	0.92
MSC	6	5.1	0.88	SNV	7	3.2	0.93
SNV	6	5.3	0.90	No treatment	8	3.1	0.94
No treatment	6	6.0	0.81	MSC	8	3.2	0.93

Table 7. WPCS laboratory (2004 and 2005) calibration performance for moisture predicting WPCS field data set (2004 and 2005) compared to a WPCS field (2004 and 2005) calibration validated using cross-validation technique.

Laboratory-Based WPCS Model		Performance Predicting Field Data		Field WPCS Model		Cross-Validation Performance	
Math Pre-treatment	PCs	RMSEP (MC % w.b.)	r	Math Pre-treatment	PCs	RMSECV (MC % w.b.)	r
MSC+SG1	5	3.4	0.81	SG1	4	3.3	0.79
SNV+SG1	5	3.4	0.82	SG2	5	3.1	0.81
SNV+SG2	5	3.4	0.82	No treatment	5	3.2	0.8
SNV	5	4.8	0.81	SNV+SG2	7	2.9	0.84
MSC+SG2	6	3.2	0.81	MSC+SG2	7	2.9	0.84
SG1	6	3.9	0.76	SNV+SG1	7	3.0	0.83
No treatment	7	3.4	0.81	MSC+SG1	8	2.8	0.85
MSC	7	3.5	0.81	MSC	9	2.8	0.86
SG2	10	6.4	0.50	SNV	10	2.8	0.85

Table 8. Alfalfa laboratory (2005) calibration performance for moisture predicting alfalfa field data[a] (2004) compared to an alfalfa field (2004) calibration validated using cross-validation technique.

Laboratory-Based Alfalfa Model (2005) Using CP04 Sensor		Performance Predicting (2004) Field Data		Field Alfalfa Model (2004) Using CP04 Sensor		Cross-Validation Performance	
Math Pre-treatment	PCs	RMSEP (MC % w.b.)	r	Math Pre-treatment	PCs	RMSECV (MC % w.b.)	r
SNV+SG2	3	3.9	0.93	SG2	3	2.5	0.95
MSC+SG2	3	4.0	0.93	SG1	3	2.7	0.94
SNV+SG1	4	3.0	0.95	SNV+SG2	4	2.4	0.96
MSC+SG1	4	3.2	0.94	MSC+SG2	4	2.4	0.95
SG1	4	3.3	0.94	SNV+SG1	4	2.5	0.95
SG2	4	4.0	0.92	MSC+SG1	5	2.4	0.96
MSC	5	3.3	0.94	MSC	6	2.5	0.95
SNV	6	4.0	0.91	No treatment	6	2.6	0.95
No treatment	7	4.0	0.92	SNV	7	2.4	0.95

[a] 2004 field reference moisture statistics: range = 27% to 77% w.b., mean = 58% w.b., and standard deviation = 8% w.b.

Table 9. WPCS laboratory (2005) calibration performance for moisture predicting WPCS field data[a] (2004) compared to a WPCS field (2004) calibration validated using cross-validation technique.

Laboratory-Based WPCS Model (2005) Using CP04 Sensor		Performance Predicting (2004) Field Data		Field WPCS Model (2004) Using CP04 Sensor		Cross-Validation Performance	
Math Pre-treatment	PCs	RMSEP (MC % w.b.)	r	Math Pre-treatment	PCs	RMSECV (MC % w.b.)	r
SNV+SG1	5	2.1	0.90	MSC+SG1	1	2.3	0.88
MSC+SG1	6	2.1	0.91	MSC	1	2.3	0.88
MSC+SG2	6	2.8	0.88	MSC+SG2	2	2.2	0.89
MSC	6	3.1	0.90	SNV+SG2	2	2.2	0.89
SG1	7	2.2	0.90	No treatment	2	2.3	0.88
SNV+SG2	7	2.9	0.88	SNV+SG1	3	2.1	0.90
SG2	8	2.6	0.88	SG1	3	2.2	0.89
SNV	8	2.9	0.90	SG2	3	2.2	0.89
No treatment	9	2.2	0.90	SNV	3	2.2	0.89

[a] 2004 field reference moisture statistics: range = 44% to 77% w.b., mean = 60% w.b., and standard deviation = 5% w.b.

to predict field data collected in 2004 accomplished this. The CP04 spectrometer was used to collect both data sets, and only these spectra were included in the calibration and validation dataset.

When predicting 2004 alfalfa field data with a 2005 alfalfa laboratory calibration, the laboratory models did not perform as well, as noted by the higher RMSEPs, 3.9 compared to 2.5 (table 8). When a 2004 WPCS field dataset was predicted using a calibration developed with 2005 laboratory data, it is evident that the laboratory calibrations did not perform as well, which is illustrated by the higher number of optimal PCs, five compared to one (table 9). Similar RMSEPs were observed, but more spectral information was required to produce these values (i.e., larger number of optimal PCs).

Predicting Moisture Independent of Crop

The ability to predict moisture independent of crop type would greatly reduce the amount of data that would be necessary to support predicting moisture on a forage harvester. A variety of crops are harvested for forage and biomass around the world. Developing calibrations for each of these crops would require an enormous effort. The comparisons to follow have been designed to assess a model's ability to predict moisture in a crop that was not used for model development.

When predicting WPCS data with a calibration developed with laboratory alfalfa data, it was apparent that the alfalfa models did not predict WPCS moisture as well as a calibration model developed with WPCS spectra (table 10). However, the number of optimal PCs was less than similar WPCS

Table 10. Alfalfa laboratory (2004 and 2005) calibration performance for moisture predicting WPCS laboratory data (2004 and 2005) compared to a WPCS laboratory (2004 and 2005) calibration validated using cross-validation technique.

Laboratory-Based Alfalfa Model		Performance Predicting Laboratory-Based WPCS Data		Laboratory-Based WPCS Model		Cross-Validation Performance	
Math Pre-treatment	PCs	RMSEP (MC % w.b.)	r	Math Pre-treatment	PCs	RMSECV (MC % w.b.)	r
SNV+SG1	4	2.7	0.96	SNV+SG1	5	1.1	0.96
MSC+SG2	4	3.1	0.95	SNV+SG2	5	1.1	0.96
SNV+SG2	4	3.2	0.95	MSC+SG1	5	1.1	0.96
MSC	5	3.1	0.97	SNV	5	1.4	0.94
MSC+SG1	5	3.1	0.97	MSC+SG2	6	1.2	0.95
SNV	6	2.0	0.95	SG1	6	1.3	0.97
No treatment	6	2.2	0.95	SG2	6	1.3	0.97
SG1	6	3.1	0.97	MSC	7	1.1	0.98
SG2	6	3.4	0.96	No treatment	7	1.3	0.94

Table 11. WPCS laboratory (2004 and 2005) calibration performance for moisture predicting alfalfa laboratory data (2004 and 2005) compared to an alfalfa laboratory (2004 and 2005) calibration validated using cross-validation technique.

Laboratory-Based WPCS Model		Performance Predicting Laboratory-Based Alfalfa Data		Laboratory-Based Alfalfa Model		Cross-Validation Performance	
Math Pre-treatment	PCs	RMSEP (MC % w.b.)	r	Math Pre-treatment	PCs	RMSECV (MC % w.b.)	r
SNV+SG1	5	3.3	0.97	SNV+SG2	4	2.5	0.97
SNV+SG2	5	3.3	0.97	MSC+SG2	4	2.5	0.97
SNV	5	3.7	0.95	SNV+SG1	4	2.7	0.96
MSC+SG1	5	3.9	0.97	MSC+SG1	5	2.5	0.97
MSC+SG2	6	3.1	0.96	SG2	6	2.6	0.97
SG1	6	3.6	0.96	MSC	6	2.7	0.96
No treatment	7	4.0	0.94	SNV	6	2.7	0.96
MSC	7	4.0	0.97	SG1	6	2.9	0.96
SG2	10	7.5	0.71	No treatment	6	3.1	0.95

models. Increasing the number of PCs to match the WPCS models did not lower the RMSEP to levels seen in the WPCS results. Therefore, predicting WPCS data with alfalfa calibration data did result in a loss of prediction accuracy. However, some models did predict moisture with the desired accuracy of ±2 percentage units.

When predicting laboratory based alfalfa data with laboratory based WPCS data, the WPCS models did not perform as well as those calibration models developed with alfalfa data, as shown by higher RMSEPs for the former calibration models (table 11). In addition, more PCs were required to produce lower RMSEPs. Therefore, it can be concluded that predicting alfalfa data with WPCS resulted in a loss of prediction accuracy.

Regional Calibration Stability

When considering various locations where forages are produced, many differences exist, including agronomic characteristics of the land, local cultural practices, and climate. The variability introduced by these differences will need to be considered when predicting moisture with NIRS across many regions.

Regional calibration stability is an important issue when considering calibration development for a global agricultural community. Support and calibration maintenance for crops grown in different regions of the world will be necessary if this technology is to be commercialized. Maintaining calibrations for each region would be very time-consuming and expensive. The purpose of the comparisons to follow was to assess regional calibration stability. The data presented were obtained through project cooperators.

Table 12. WPCS field (2004 and 2005) calibration model for moisture developed with Wisconsin data predicting California WPCS field (2005) data.[a]

Wisconsin Field WPCS Calibration		Performance	
Math Pre-treatment	PCs	RMSEP (MC % w.b.)	r
SNV+SG2	2	11.7	0.41
MSC+SG2	2	11.8	0.41
MSC	3	13.9	0.43
SG2	4	7.9	0.57
SNV+SG1	4	8.7	0.49
MSC+SG1	4	8.7	0.50
SNV	4	13.9	0.43
No treatment	5	12.7	0.50
SG1	6	8.3	0.41

[a] 2004 California field reference moisture statistics: 72 samples, range = 60% to 80% w.b., and mean = 73% w.b.

The following comparisons were generated using the Wisconsin-based WPCS field calibration (table 3) and data collected in Arizona and Bavaria, Germany, by project cooperators. These cooperators used the same sensors, harvesters, and sample preparation procedures. RMSEPs were high when predicting Arizona and California WPCS samples with this model (tables 12 and 13). The poor performance could be the result of many factors, including differences in climate, ambient conditions at the time of harvest, or physiological effects associated with development of an irrigated crop. The results of predicting the Bavarian dataset were a great deal better, performing as well as the cross-validation results of the calibration model (table 14). This would lead one to conclude that the crop and ambient conditions in Bavaria are

Table 13. WPCS field (2004 and 2005) calibration model for moisture developed with Wisconsin data predicting Arizona WPCS field (2005) data.[a]

Wisconsin Field WPCS Calibration		Performance	
Math Pre-treatment	PCs	RMSEP (MC % w.b.)	r
MSC+SG2	2	5.0	0.84
SNV+SG2	2	5.0	0.85
MSC	3	6.4	0.78
SNV	4	4.8	0.83
SG2	4	4.9	0.91
SNV+SG1	4	6.0	0.78
MSC+SG1	4	6.4	0.78
No treatment	5	4.5	0.82
SG1	6	4.4	0.84

[a] 2005 Arizona field reference moisture statistics: 65 samples.

Table 14. WPCS field (2004 and 2005) calibration model for moisture developed with Wisconsin data predicting Bavarian WPCS field (2005) data.[a]

Wisconsin Field WPCS Calibration		Performance	
Math Pre-treatment	PCs	RMSEP (MC % w.b.)	r
MSC+SG2	2	3.6	0.87
SNV+SG2	2	3.6	0.87
MSC	3	2.4	0.87
SNV	4	2.3	0.87
SG2	4	3.0	0.84
MSC+SG1	4	3.7	0.82
SNV+SG1	4	4.0	0.81
No treatment	5	3.8	0.85
SG1	6	2.8	0.84

[a] 2005 Bavarian field reference moisture statistics: 206 samples, range = 53% to 80% w.b.

more similar to Wisconsin than the conditions in Arizona and California.

Conclusions

A mobile, diode array NIR spectrometer was integrated into the spout of a self-propelled forage harvester to measure crop moisture. Spectra and moisture reference samples were collected in 2004 and 2005 for the development of laboratory and field-based moisture calibrations. From this research, we can conclude:

- Moisture prediction models for whole-plant corn silage (WPCS) developed using laboratory data had an RMSECV of 1.1% using five PCs, while a calibration developed using field data had an RMSECV of 3.3% using four PCs.
- Alfalfa validation results were slightly worse, with RMSECVs of 2.5% using four PCs and 3.7% using three PCs for models using laboratory and field data, respectively.
- The Corona prototype sensor prediction performance was similar to that of the commercially available Corona 45 sensor.
- Math pre-treatments were found to improve model performance by reducing the number of PCs and lowering RMSECVs. In general, schemes employing both derivative and scatter correction provided the best results.
- Models developed with laboratory data could predict forage moisture from spectra collected in the field with about the same level of performance (RMSEP) as a model developed with field data. However, the models developed with laboratory data required more spectral information to obtain similar measures of calibration effectiveness.
- When predicting data independent of crop, it was evident that models developed with alfalfa data were more successful in predicting WPCS moisture than models developed with WPCS were at predicting alfalfa moisture. This is likely due the larger variability represented by the alfalfa dataset.
- The question of regional calibration stability was addressed through comparisons of data collected in Wisconsin, California, Arizona, and Bavaria, Germany. The Wisconsin-based calibration performed well on the Bavarian dataset, but poorly on the Arizona and California data, indicating that the crop and ambient conditions in Bavaria are more similar to Wisconsin than the conditions in Arizona and California.

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NOMENCLATURE

CP04	= 2004 prototype spectrometer
CP05	= 2005 prototype spectrometer
C45	= Corona 45 NIR spectrometer
InGaAs	= indium gallium arsenide
MC	= moisture content, wet basis
MSC	= multiplicative scatter correction (math pre-treatment)
NIRS	= near-infrared reflectance spectroscopy
PCs	= principal components
PLSR	= partial least squares regression
RMSECV	= root mean standard error of cross-validation
RMSEP	= root mean standard error of prediction
SG	= Savitzky-Golay
SNV	= standard normal variate (math pre-treatment)
WPCS	= whole-plant corn silage
SG1	= Savitzky-Golay first derivative
SG2	= Savitzky-Golay second derivative