Near Infrared reflectance spectroscopy for management and utilization of forages

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Abstract

Rapid on-farm forage analysis with near infrared spectroscopy (NIRS) is changing the way producers manage and utilize forages. NIRS moisture prediction has been demonstrated to accurately predict forage moisture on the harvester where other technologies (*viz.* conductive, capacitive, microwave) have struggled with the heterogeneous nature of these biological materials. Furthermore, NIRS has demonstrated its ability to move the information beyond moisture to the inclusion of forage compositional factors opening the possibility to use NIRS for plant nutrient management and precision diet composition.

Introduction

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 research has been to aid the forage producer in the prediction of crop moisture. Moisture prediction guides decisions regarding harvest and storage of forage crops, minimizes production costs and maximizes forage quality. Management decisions influenced by moisture level include deciding optimum harvest time, determining targeted use of silage, choosing storage method, and optimizing harvester setup and site-specific crop management.

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 the concentration of desired constituents. These analyses are conducted world-wide in laboratories linked together with calibration networks.

The technology used on today’s farms owes its success to the same physical and chemical theory that enables laboratories to provide accurate constituent information of agricultural products. However, 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.

Theory

NIRS is based on selective absorption of light energy in the near infrared region of the electromagnetic spectrum (EMS). The near infrared region is defined as the wavelengths of light between 780 and 2500 nm. Near infrared light energy is selectively absorbed based upon the molecular makeup of the material and the frequency of the light energy. Molecular absorption of light energy in the NIR region is primarily due to stretching, bending, or deformation of X-H bonds where X is carbon, nitrogen, or oxygen (Fahey et al., 1994). These bonds are particularly useful in determining the composition of organic materials such as forages.

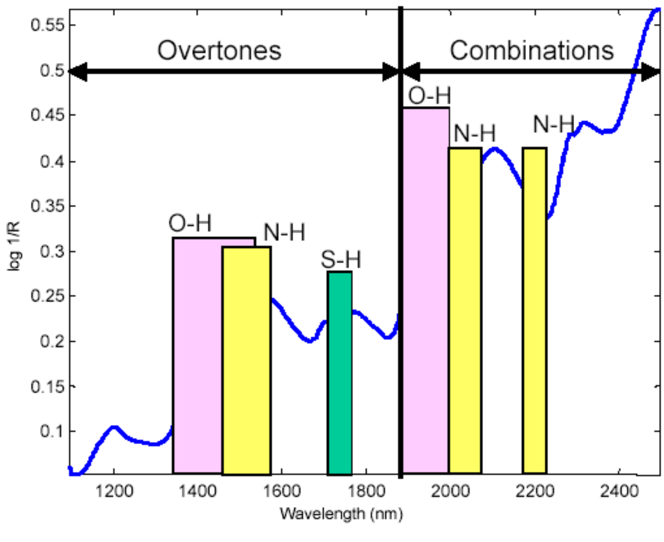

Figure *Erro! Nenhum texto com o estilo especificado foi encontrado no documento.***:** Overtone and combination absorption bands for X-H bonds (Bertrand, 2002).

The near infrared region encompasses these combination and overtone bands, providing rich spectral information that can be related to molecular composition. Energy in the near infrared region is not as strongly absorbed as in the mid infrared region, enabling measurement of light absorption indirectly by light reflection. The relationship between absorbed and reflected light is given by the Beer-Lambert Law which states that the amount of light energy diffusely reflected is nearly proportional to the light absorbed. Here absorbance is described as the quotient of the incident light I_0 and reflected light I_R. The relationship between light reflected and light absorbed is the principle relationship governing reflectance spectroscopy and the near infrared (NIR) spectrometer (Figure 2).

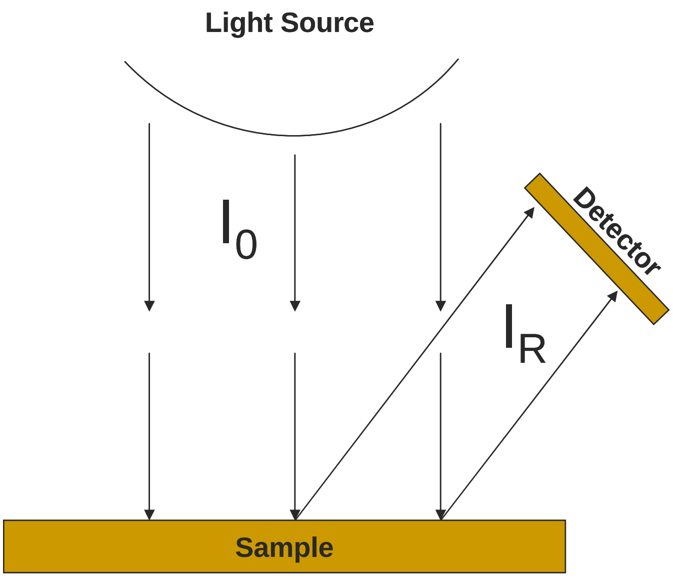

Figure 2: Basic reflectance spectrometer layout.

In this basic spectrometer, there is a light source that provides a stable light intensity to interact with the sample I_0. Some of the light from the source is absorbed, transmitted, scattered by the sample surface, reflected, and diffusely reflected. The diffusely reflected light I_R energy is measured at some angle with respect to the source by the detector.

The method of measuring individual wavelengths of light is dependent on the type of spectrometer utilized. There are two main methods. In the first, sequential instruments, commonly used in forage testing laboratories to measure the wavelengths of light, are indexed by a filter wheel that is located at either the light source or the detector (Figure 3). These instruments filter polychromatic light into monochromatic light so that a known wavelength of light only exists at the detector. This information is then detected by a lead sulfide (PbS) detector and light intensity is recorded for each wavelength.

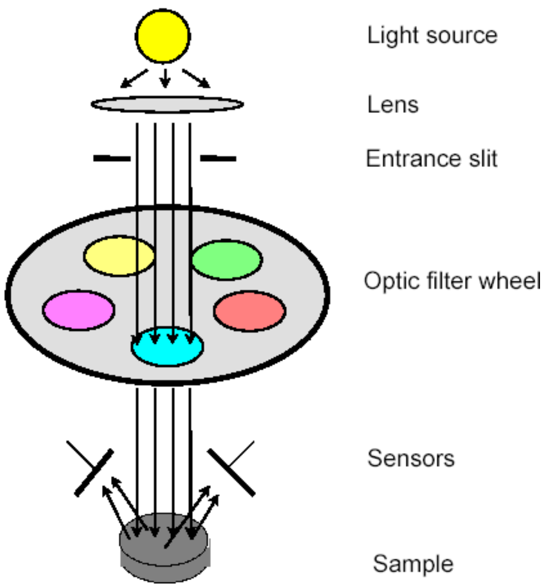

Figure 3: Sequential NIR spectrometer (Bertrand, 2002).

The second method commonly used for … involves a multichannel spectrometer which measures all detectable wavelengths of light simultaneously (Figure 4). In this spectrometer, polychromatic light illuminates the sample and is partitioned into its component wavelengths by a monochromator, or grating. The wavelengths are then presented to a photodiode array which simultaneously measures the intensity corresponding to each wavelength of light.

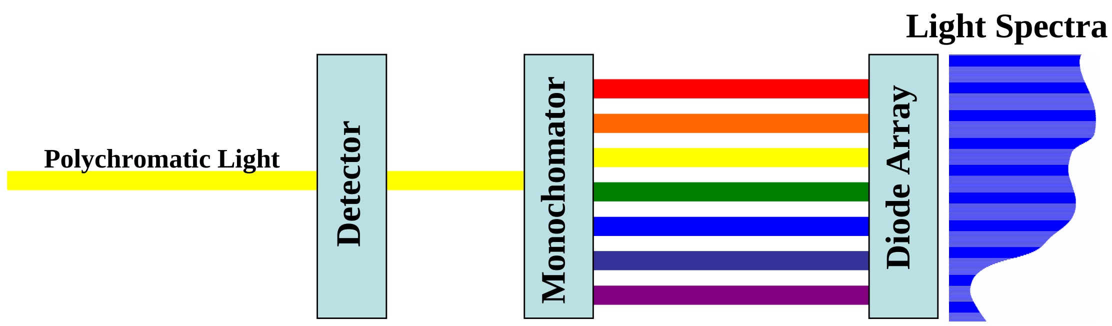

Figure 4: Diode array spectrometer.

The detectable wavelength range of the spectrometer is dependent on the material properties of the photosensitive diodes. Typical diode array materials include silicon (Si), lead sulfide (PbS), and indium gallium arsenic (InGaAs). The resolution of the spectrometer is a function of the size of the diode array and the detectable wavelength range. Unlike sequential instruments, diode array spectrometers have no moving parts. These spectrometers produce spectra nearly instantaneously and are very robust, lending them to be useful for on-harvester applications (Paul, 2003).

In summary, it can be shown that the molecular composition of a material can be determined by the type of light energy absorbed. This light energy is only a function of the wavelength of the light. Light is absorbed if the energy is equal to a molecular energy level of the molecule, which is a function of the bond strength and atomic mass of the atoms that make up the molecule. This phenomenon provides the basis for NIRS as absorbed wavelengths of light can be indirectly measured as the intensity of the wavelengths reflected. These reflection spectra contain a great deal of information regarding the molecular composition of the material being measured.

Applications

NIRS for yield-mapping and documentation

Early farming techniques were small scale and the labor of working the soil, planting and maintaining proper nutrition for the crop was completed manually. This intimate contact between the farmer and his crop enabled him to spatially identify crop needs, allowing him to meet these needs on a site-specific basis. In the late 1800s this intimacy was altered by the advent of modern farm equipment. Farm machinery greatly increased farm productivity, but the close relationship that once existed between the crop and the farmer was lost. The farmer now managed the crop on a field-by-field basis, greatly reducing the resolution when determining and meeting a specific plant's needs (Kuhar et al., 1997). Modern technology has sought to remedy this challenge associated with large scale farming. Two major developments can be credited with increasing the producer's field resolution: the miniaturization of modern computing technology and the deployment of the NAVISTAR satellite array by the U.S. Department of Defense. NAVISTAR provided a global positioning system (GPS) for military and civilian use. Mobile computers and GPS technology enabled producers to link agronomic and yield data spatially, enabling site-specific prescription of nutrients and soil amendments.

This technology has been adapted to aid in production of many types of crops such as vegetables, citrus, cereal grains, and forages. In forages, however, one key component has been missing. Forage crop yield is usually expressed in terms of kg DM/ha as any variation in moisture that may exist in harvested crop would skew yield results when considering yield on a wet basis. Correcting for moisture in forages has been challenging because it requires a method of rapidly determining moisture content of a non-uniform crop stream with a very short residence time in the harvester.

A technology for rapid determination of moisture in forages would enable yield-mapping technologies to be used in management of forage crops. Yield maps could be used in conjunction with site-specific technologies in application of soil amendments, fertilizers, and pesticides to determine the resulting yield response for these management decisions. Yield maps in multiple cutting systems would enable the producer to modify inputs affecting crops, thus allowing the farmer to monitor yield response as soon as 30 days from application. Yield improvement would not be the only factor increasing profitability as site-specific application of fertilizer and pesticides could lead to lower usage, resulting in lower input costs and environmental impact.

Having precise yield information would also provide the producer with an accurate inventory of the harvested crop. This information would allow ration formulation based on forage inventory. The yield information system would provide the producer accurate records, enabling forage production costs and inputs to be closely managed. For a cash crop operation, precise recordkeeping would not only provide the same management and inventory benefits as for a dairy producer but would also provide information about his product, allowing him to demand premiums for high quality forage.

NIRS for storage of forage.

Forage availability does not always correspond to animal needs. To overcome this problem, modern agriculture has developed methods of storing forage. The storage of forage has provided a consistent food supply through non-growing seasons. Storing forage as an ensiled material is highly dependent on creating an anaerobic environment that promotes fermentation. The success of this storage method is dependent on many factors, including moisture, density, oxygen available, pH, and presence of certain microorganisms.

Moisture is one of the primary factors affecting the storage of forage as moisture content at harvest directly affects dry matter losses during storage (Figure 5).

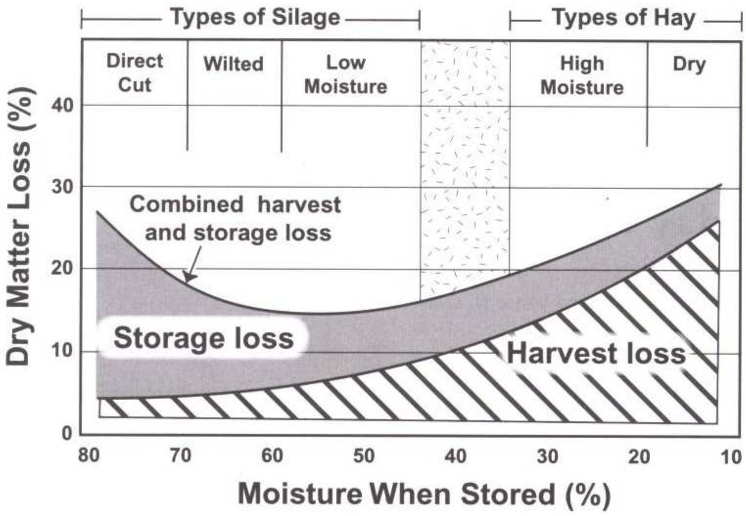

Figure 5: Forage losses as a function of moisture content at harvest (Barnes et al., 2003).

Silages high in moisture also increase the development of clostridia and other undesirable bacteria. These organisms produce butyric acid and amines that reduce animal intake and increase dry matter losses (Figure 6). Properly wilting forage will minimize the amount of fermentable carbohydrates required to raise the acidity. Raising the acidity is essential to the preservation of the forage and the restriction of the development of undesirable microorganisms. In extremely high-moisture forage, nutrients can also be carried away by water seepage, or effluent, as the forage is compressed in the storage structure (Barnes et al., 2003).

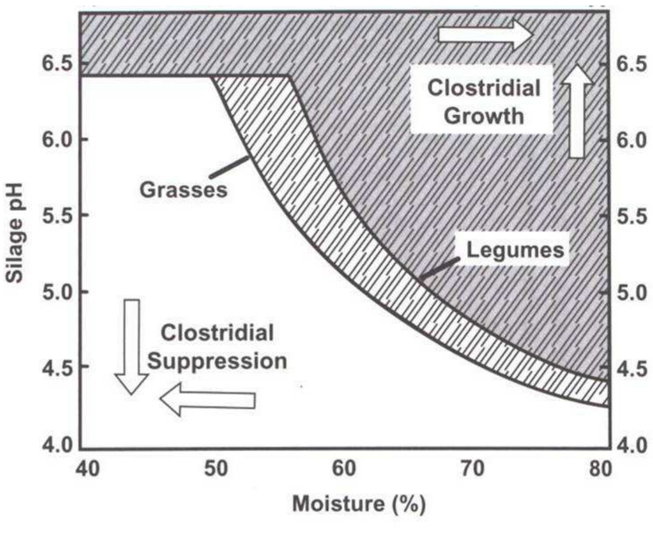

Figure 6: Unfavorable bacterial growth as a function of moisture content in ensiled forage (Barnes et al., 2003).

Alternatively, if forage moistures are too low, losses may occur as the result of low forage density in storage. Low forage density promotes aerobic respiration, yielding bacterial and mold growth. This process increases the temperature of the forage and is known as heating. The heating of forage uses sugars and reduces protein digestibility. In severe cases, spontaneous combustion may result.

There are many factors that prevent producers from storing forage at the proper moisture. The producer cannot control some factors such as weather and ambient drying conditions. Other factors could be controlled if certain tools existed, such as an instrument that efficiently measures forage moisture. A rapid and accurate method of determining forage moisture would enable a producer to make storage decisions based upon current conditions and impending weather.

A rapid means of predicting forage moisture could be possible through near infrared reflectance spectroscopy (NIRS). NIRS would aid the producer by monitoring current harvest conditions, allowing him to switch locations or to mix fields based upon moisture. Having an accurate dry matter (DM) mass flow rate through the harvester could aid in applying the proper amount of forage amendments and inoculants, potentially reducing the costs associated with these treatments. This tool could greatly enhance the producer's ability to provide optimal conditions when ensiling forage.

NIRS in feeding of forage

If accurate records of feed inventory are to be maintained, then accurate removal rates for stored forages must be included in the assessment. The NIR sensor in stationary mode would allow for the rapid determination of forage moisture content as it is removed from storage. This would enable the producer to compare removal rates to storage inventories from previously recorded yield data.

TMR rations are balanced considering the amount of dry nutrients present in forages. However, forages are fed based upon their weight when removed from storage. This method assumes a uniform moisture content in the forage removed for that particular feeding or week of feeding, depending on the frequency of DM correction. However, DM in corn silage has been found to vary five to six percentage units in consecutive weeks (Holter, 1983). Variations are especially large in horizontal silos (Mertens and Berzaghi, 2009).

In 2004, Stone conducted a study to investigate DM variation in horizontal silos (Stone, 2004). Stone's research included sampling nine haylage and eleven corn silage bunker silos in central New York. He found that typical variations in the haylage bunkers were so great that a feeder could deliver an entirely different ration during the same day if care was not taken when loading feed. He concluded that not only does DM need to be assessed frequently, but care must be taken when sampling to ensure the bunker is accurately represented.

During a precise feeding experiment, Mertens and Berzaghi (2009) measured the daily variation in silage composition for both an alfalfa and corn silage bunker (Figure 7). Although the bunkers were mechanically defaced, thereby reducing variation, substantial daily variation was observed. Mertens and Berzaghi attribute abrupt changes in DM to rain or snow precipitation that contaminated the silage before mixing and feeding.

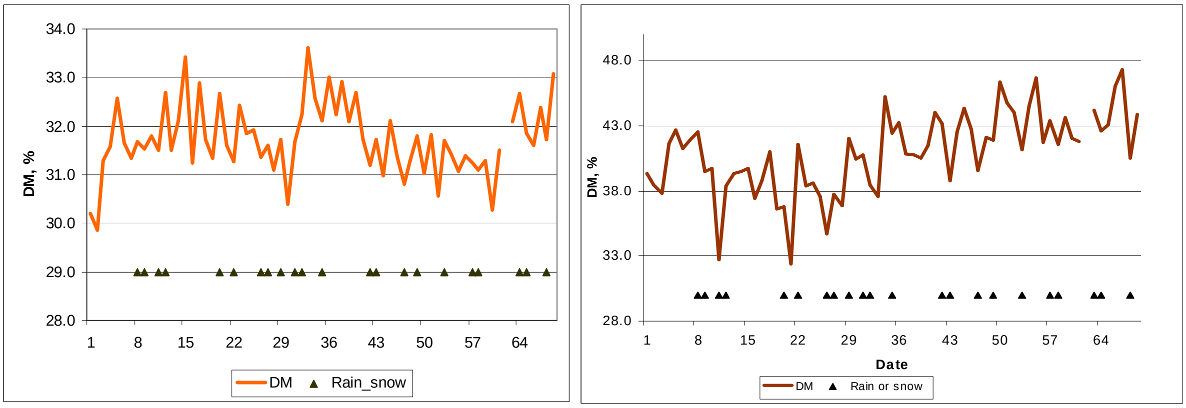

Figure 7: Variation in horizontal silage dry matter over a two-month feed-out period (Mertens and Berzaghi, 2009).

It is recommended that forages fed in total mixed ration (TMR) with less than 75% DM be corrected for DM content each week as variability in stored forage moisture content can result in unbalanced rations if not considered in ration formulation (Linn, 1995). A ten percent increase in forage DM content would result in a 0.1 lb decrease in crude protein intake. Crude protein intake is directly proportional to milk protein levels (Linn, 1995). Low DM content can also lead to off-feed and acidosis problems (Nordlund, 2003).

Current tools for analysis of forage moisture require drying the forage and determining the moisture content gravimetrically (Oetzel et al., 1993). These methods are time consuming and cumbersome. It has been found that few farmers practice these methods of DM determination but rather use animal intake at the bunk to adjust forage concentrations in the TMR (Nordlund, 2003). A stationary NIR sensor would provide a producer a rapid method of correcting his ration for DM each feeding.

Our research – on-harvester prediction of moisture via NIRS

Water content is a major factor influencing successful fermentation when ensiling forage. Thus, our research focused on the investigation of NIRS technology to meet the challenge of predicting moisture in real time on the forage harvester (Digman, 2006; Digman and Shinners, 2008). The feasibility of this technology was investigated through calibration development and verification. The research goal was to develop a moisture calibration that will be insensitive to the variability expected in mobile forage harvesting. Moisture prediction will guide decisions regarding harvest and storage of forage crops, minimizing production costs and maximizing forage quality.

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, Dairy Forage Research Center Farm (USDA-ARS), and several dairies in southwest Wisconsin and California for the development of static (in-lab) and dynamic (on-harvester) moisture calibrations (Figure 8). These locations provided much variability in ambient, harvesting and agronomic conditions. Data were also obtained from other researchers in Arizona, Bavaria and Zweibrücken, Germany.

***Figure 8*:** Prototype NIRS sensor mounted on forage harvester spout.

The following two criteria were used when comparing individual calibrations or the effectiveness of certain math pre-treatments. Math pre-treatments are transformations of the spectra used to remove non-constituent spectral information. Each calibration was ranked first by the number of principal components (PCs) as identified by the software program used to develop the calibration (Unscrambler). The fewer PCs, the less spectral information 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 over-fit to the data used for 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 a RMSEP(CV) of less than two moisture percentage points.

Moisture prediction models for whole-plant-corn-silage (WPCS) developed using static data had a RMSECV of 1.12% using five PCs while a calibration developed using dynamic data had a RMSECV of 3.28% using four PCs. Alfalfa validation results were slightly worse with RMSECVs of 2.50% using four PCs and 3.74% using three PCs for models using static and dynamic data, respectively.

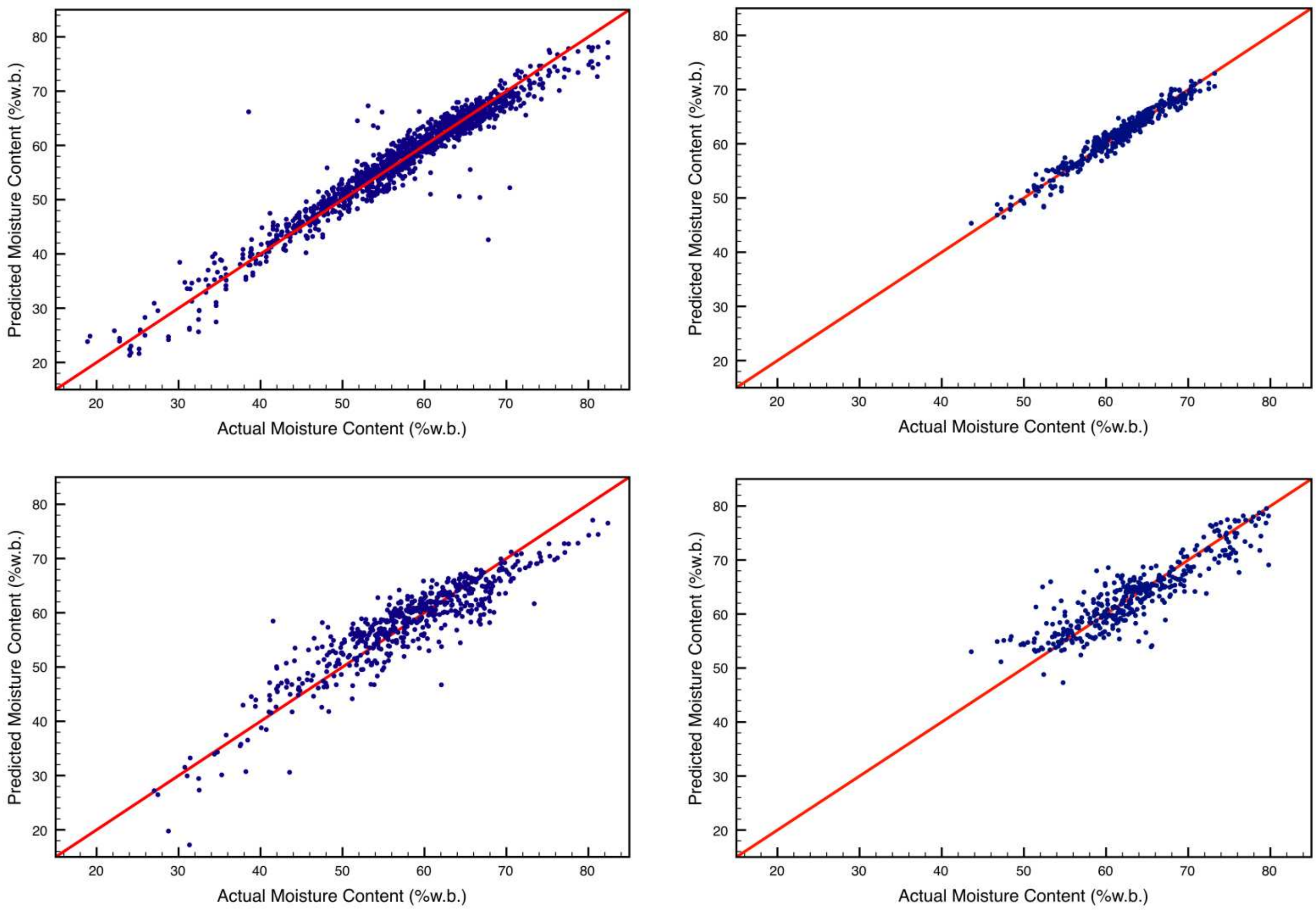

Figure 9: Calibration performance depicted as predicted vs. actual moisture content (%w.b.) for best performing models including alfalfa laboratory (top left), whole plant corn silage laboratory (top right), alfalfa field (bottom left) and whole plant corn silage field (bottom right).

Predicting dynamic data with a model developed using static data would greatly reduce overhead associated with collecting dynamic calibration data and would increase the mobility of the data collection effort because the harvester would not be needed. Dynamic data were predicted with calibrations developed using static data with similar performance as defined by root mean standard error (RMSE). In models with similar RMSEs, more spectral information was required to obtain similar measures of calibration effectiveness as evidenced by the larger number of PCs required for these models. A static alfalfa model predicted dynamic data with a RMSEP of 3.41% using 4 PCs compared to the dynamic model's RMSECV of 3.74% using 3 PCs. Similar results were found with WPCS models.

The ability to predict moisture independent from the crop would greatly reduce the amount of data that would be necessary to support predicting moisture on a forage harvester. When predicting data independent from the 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.

Understanding the influence that spectrometer hardware has on a calibration's ability to predict moisture should be considered when spectrometer hardware is upgraded in the future. Three sensors were used in this research, a Corona 45 (C45), and two Corona prototypes (CP04 and CP05). Principal component analysis showed the Corona 45 (C45) and 2004 Corona prototype (CP04) produced similar spectra while the spectra from the 2005 Corona prototype (CP05) was slightly different than the other two sensors. This did translate into better calibration transferability between the CP04 and C45 than the CP04 to the CP05 when comparing RMSEPs and PCs for prediction of moisture on a validation dataset. From this experiment it does appear that calibrations can be transferred between spectrometers depending on the spectrometer hardware and math pre-treatment method.

The question of regional calibration stability was addressed through comparisons of data collected in WI, CA, AZ and Bavaria, Germany. The WI developed WPCS dynamic calibration performed quite well on the Bavarian WPCS dataset with an RMSEP of 3.58%. However, poor performance was seen on data collected in the western U.S. with RMSEPs ranging from 11.71% and 4.97% for AZ and CA WPCS data, respectively.

Two fractional factorial experiments were conducted to investigate calibration robustness. First, static calibration robustness due to moisture content, mean particle size (MPS) and temperature was investigated. It was found that moisture prediction performance was variable, depending on the math pre-treatment scheme employed. Two math pre-treatment schemes were found to not only provide the lowest RMSEPs but were also insensitive to the influence of the factors explored.

Next, dynamic calibration robustness was investigated using a fractional factorial experiment evaluating MPS, lens angle, and position on spout (POS). Moving the sensor to the aft location of the spout greatly reduced the reflection intensities recorded by the spectrometer. This phenomenon lead the POS factor to be the most significant factor identified in this investigation. Math pre-treatment did lower the RMSEPs but did not successfully eliminate the effect of the POS factor.

In 2005, a small dataset was collected to determine the feasibility of developing a calibration for predicting MPS. The results of this investigation demonstrated a MPS calibration is feasible both statically and dynamically with RMSECVs of 2.1 mm using 4 PCs and 2.1 mm using 6 PCs, respectively.

Although not part of our work, Kormann and Flohr evaluated three NIR spectrometers for measurement of forage moisture on a commercial forage harvester. They explored the feasibility to extend on-harvester NIR capabilities to predict protein and starch with SECVs of .28% and 1.62% respectively (Kormann and Flohr, 2002). This work demonstrates that predicting diet composition and harvest nutrient removal is possible with on-farm NIRS. Forage composition prediction will provide the producer essential data to precisely manage nutrient cycling from the field to the animal reducing production costs and the environmental impact.

Conclusions

Moisture prediction models for whole-plant-corn-silage (WPCS) developed using laboratory data had a RMSECV of 1.1% using five PCs while a calibration developed using field data had a 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. 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.

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Addendum

Since the publication of this research two commercial NIRS products have been marketed for forage management (Table 1). The use of trade, firm, or corporation names in this publication is for the information and convenience of the reader. Such use does not constitute an official endorsement or approval by the United States Department of Agriculture or the Agricultural Research Service of any product or service to the exclusion of others that may be suitable.

Table 1. Commercially available NIRS for on-farm forage management

Product	Company	Headquarters
AgriNIR	dinamica generale srl	Mantova, Italy
HarvestLab	Deere & Company	Moline, Illinois, U.S.A.

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