Field Crops Research 222 (2018) 189–196

Contents lists available at ScienceDirect

Field Crops Research

journal homepage: www.elsevier.com/locate/fcr

Estimating alfalfa yield and nutritive value using remote sensing and air temperature

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ARTICLE INFO

Keywords:
Alfalfa yield
Alfalfa quality
Canopy reflectance
Growing degree units
Remote-sensing applications

ABSTRACT

In-field estimation of alfalfa (*Medicago sativa* L.) yield and nutritive value can inform management decisions to optimize forage quality and production. However, acquisition of timely information at the field scale is limited using traditional measurements such as destructive sampling and assessment of plant maturity. Remote sensing technologies (e.g., measurement of canopy reflectance) have the potential to enable rapid measurements at the field scale. Canopy reflectance (350–2500 nm) and Light Detection and Ranging (LiDAR)-estimated canopy height were measured in conjunction with destructive sampling of alfalfa across a range of maturities at Rosemount, MN in 2014 and 2015. Sets of specific spectral wavebands were determined via stepwise regression to predict alfalfa yield and nutritive value and models were reduced by spectral range to improve utility. Cumulative growing degree units (GDUs) and canopy height were tested as model covariates. An alternative GDU calculation (GDU_{ALT}) using a temporally graduating base temperature was also tested against the traditional static base temperature. The inclusion of GDU_{ALT} increased prediction accuracy for all response variables by 9–17%. Models using a common set of seven wavebands, combined with GDU_{ALT}, explained 81–90% of the variability in yield, crude protein (CP), neutral detergent fiber (NDF), and NDF digestibility (NDFd; 48-h in-vitro), respectively. This research establishes potential for remote sensing measurements to be integrated with air temperature information to achieve rapid and accurate predictions of alfalfa yield and nutritive value at the field scale for optimized harvest management.

1. Introduction

Alfalfa is the most valuable and intensively produced perennial forage crop in the United States, and precise management to achieve forage yield and quality goals is critical to optimize profitability (Bouton, 2007). Indices of nutritive value such as relative forage quality (RFQ) can decline up to 5 index points per day (Undersander et al., 2010), which equates to an economic loss of 4–8 USD Mg alfalfa^{-1} d^{-1} in hay value (Szafranski and Martens, 2017), or a dairy productivity loss of approximately 25 kg milk Mg^{-1} d^{-1} (Undersander et al., 2016). These implications on economic value and animal productivity necessitate accurate in situ estimations of alfalfa yield and nutritive parameters. Furthermore, pre-harvest insight to nutritive value and yield can enable real-time management responses to fluctuating market conditions or feed needs. Therefore, methods capable of rapid and accurate predictions at the field-scale are needed to improve the economic efficiency and resilience of alfalfa production.

Several methods have been reported for in situ estimations of alfalfa yield and nutritive value. These include estimations based on 1) air temperature quantified as Growing Degree Units (GDUs), 2) alfalfa morphological development, and 3) remote sensing measurements. Maturity-based estimations are seldom representative of an entire field;

Abbreviations: ADF, acid detergent fiber; CARI, Chlorophyll Absorption Ratio Index; CP, crude protein; $GDU_{base\text{-}5}$, cumulative growing degree units since last alfalfa harvest (base temperature = 5 °C); GDU_{ALT}, cumulative growing degree units since last alfalfa harvest base temperature graduating from 3.5 °C (1 April) to 10 °C (31 July) and static at 10 °C through the remainder of the year; GNDVI, Green Normalized Difference Vegetation Index; MSC, mean alfalfa stem growth stage by count; MSW, mean alfalfa stem growth stage by weight; MTCI, MERIS Terrestrial Chlorophyll Index; NDF, neutral detergent fiber; NDFd, neutral detergent fiber digestibility (48-h in-vitro); NDLI, Normalized Difference Lignin Index; NDNI, Normalized Difference Nitrogen Index; NDVI, Normalized Difference Vegetation Index; NIR, wavebands within the near-infrared region of the electromagnetic spectrum (751–1100 nm); PRI, Photochemical Reflectance Index; REIP, Red Edge Inflection Point; SWIR, wavebands within the near-infrared region of the electromagnetic spectrum (1101–2500); UTILITY, set of seven common wavebands identified to predict all four dependent variables; VIS, wavebands within the visible region of the electromagnetic spectrum (350–750 nm)

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https://doi.org/10.1016/j.fcr.2018.01.017
Received 17 August 2017; Received in revised form 14 January 2018; Accepted 15 January 2018
Available online 10 April 2018
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whereas remote measurement of canopy reflectance can achieve rapid, direct assessment of a crop at field scale. However, the costs of these technologies are currently prohibitive in on-farm applications. The cost of spectral measurement technology increases with greater spectral range and resolution of the instrument. Therefore, applications may be developed that use fewer wavebands at lower spectral resolution, and may be combined with environmental data such as air temperature to improve the affordability and utility of these technologies.

Cumulative GDUs have been used previously to estimate both alfalfa yield (Smeal et al., 1991) and nutritive value (Kratchunov and Naydenov, 1995; Sulc et al., 1999). Traditional GDU calculations for alfalfa use a static base temperature (T_b) of 5 °C; however, Sharratt et al. (1989) reported that the optimum T_b for alfalfa may change throughout the growing season from 3.5 °C early in the growing season to 10 °C later in the summer. Predictions of nutritive value based only on cumulative GDUs have limited accuracy (Sulc et al., 1999), but the use of a modified GDU scale has not been investigated for predictions of alfalfa nutritive value. Advantages of using air temperature are that it is generally free and easily accessible, and that applications can be automated to use real-time information.

Visual estimations of morphological development were traditionally used to decide timing of harvest. For example, the decision to harvest alfalfa may be made when a visual assessment determines that 10% of the plants are flowering. To improve the accuracy of these estimations, Kalu and Fick (1981) assigned a numeric scale to distinct growth stages. Indices are calculated as the average growth stage weighted by number of stems [mean growth stage by count (MSC)] or plant mass within each maturity group [mean growth stage by weight (MSW)]. Kalu and Fick (1983) found that MSW provided accurate predictions of alfalfa CP, NDF, acid detergent fiber (ADF), and lignin with R^2 ranging 0.84–0.95. Hintz and Albrecht (1991) showed that predictions based on node number and plant height can provide more rapid predictions with accuracy similar to or greater than MSC and MS Owens et al. (1995) reported that using the PEAQ (Predictive Equations for Alfalfa Quality) system based on maturity of the most mature stem, along with the height of the tallest stem, provided accurate estimates of NDF and ADF (R^2 = 0.72), but are less predictive for CP (R^2 = 0.37). Additionally, Lyons et al. (2016) showed potential for alfalfa height to predict yield (R^2 = 0.66). These methods have been consistently demonstrated as valuable indicators, although it is difficult to accurately represent an entire field using contact measurements, considering time and labor requirements. Furthermore, the accuracy of these methods may vary across environmental conditions (Sanderson, 1992) and may not be applicable to new reduced-lignin alfalfa cultivars.

Remote sensing technologies include measurement of canopy reflectance, infrared measurement of canopy temperature, and LiDAR- or SONAR-based estimates of height. Precision crop management tools such as remote sensing are being developed and implemented in many crops as technology becomes more affordable and specific applications are developed (Mulla, 2013). Spectral vegetative indices (SVIs) are functions of canopy reflectance developed to assess ground cover, crop health, drought stress, and nutrient deficiencies in several major crops. These remote sensing tools can be integrated into Unmanned Aerial Vehicle (UAV) platforms to enable real-time assessments of crop nutritive value parameters at the field scale (Zhang and Kovacs, 2012). Recent research has demonstrated the potential for measurement of canopy reflectance to predict nutritive value in alfalfa monocultures (Starks et al., 2016) and perennial forage grasses (Starks et al., 2006). Starks et al. (2016) report predictions based on canopy reflectance to explain 77–83% of variation in CP, NDF, and ADF. In addition to measurement of canopy reflectance, ultra-sonic or LiDAR technology can enable remote measurement of crop height and facilitate improved estimations of crop biomass (Pittman et al., 2015). Additionally, crop height is related to alfalfa nutritive value (Owens et al., 1995). However, these technologies have not been integrated into applications to inform harvest decisions and their efficacy has not been compared to predictions based on morphological development or GDUs.

These methods of in situ crop assessment vary in accuracy and utility. The development and efficacy of models using simplified remote measurements requires further investigation, and these remote sensing approaches have not been tested in combination with temperature-based estimations. This research explores the potential for simplified remote sensing tools integrated with environmental data for more affordable applications. The objectives were to 1) develop a method for selecting specific canopy reflectance wavebands to estimate alfalfa yield and nutritive value, 2) determine the predictive value of reduced models that use fewer parameters, 3) compare utility of remote estimations to traditional assessment methods based on phenological stage and GDU accumulation, and 4) test the value of integrating environmental information such as air temperature with canopy reflectance and remotely-estimated canopy height. Our hypotheses were that 1) a set of specific wavebands of easily measureable range and resolution can be identified and used to predict alfalfa yield and nutritive value in situ, 2) the accuracy of these remote estimations will be comparable to traditional assessment methods, and 3) the integration of environmental growth indicators (cumulative GDUs) with remote measurements can provide greater prediction accuracy than these methods used alone.

2. Materials and methods

2.1. Field experiments

Field experiments were conducted in 2014 and 2015 at the University of Minnesota Research and Outreach Center in Rosemount, MN (44°42′37.34″N 93°06′10.61″W) on a Waukegan silt loam (fine-silty over sandy or sandy-skeletal, mixed, superactive, mesic Typic Hapludolls). Sites were fertilized with potassium (K) and sulfur (S) according to soil requirements for alfalfa production (Kaiser et al., 2011), and irrigated to meet monthly average precipitation levels. Air temperature and precipitation data were obtained from a weather station located within < 1 km of the experiments.

Data were collected from three different fields of alfalfa at varying times throughout the study (Table 1). Each alfalfa stand had sufficient plant density for optimum production (> 50 plants m^{-2}) (Sheaffer et al., 1988) which was determined by counting plants in a m^2 quadrant at four random locations from each of the sites. In 2014, all alfalfa was cut at a height of 5 cm above the soil and removed from the plot areas (30 × 38 m) on 31 July. Each site was divided into a completely randomized design with four replications and 16 plots (1.8 × 4.6 m) per replication. Measurements of canopy reflectance were recorded in conjunction with destructive sampling on 3- to 4-d intervals. At each sampling event, one plot in each replication was sampled and each plot was sampled only once, resulting in 16 sampling dates.

The experimental design was modified in 2015 to include 12 replications with 10 plots (1.8 × 1.8 m) per replication. All alfalfa was cut at a height of 5 cm above the soil and removed from one plot per replication on 3- to 4-d intervals for 10 harvest dates, resulting in a range

Table 1
Experimental site descriptions and sampling timeline.

Year	Growth period sampled	Alfalfa variety	Year planted	Site ID	Replications per site
2014	15 Aug–15 Oct	Dekalb '4401-RR'	2013	1	4
	15 Aug–15 Oct	Pioneer '55V12'	2012	2	4
2015	15 Apr–16 Jun	Dekalb '4401-RR'	2013	1	12
	3 Jul–20 Aug	Dekalb '4401-RR'	2013	3	12

of phenological stages represented simultaneously in the experiment. Approximately 1 wk following the final cutting date, remote sensing measurements and destructive samples were taken from all plots in six of the 12 replications. Remote sensing measurements and samples were collected from the remaining six replications approximately 10 d later. This process resulted in measurements from 20 discrete levels of regrowth ranging from 9 to 62 d since cutting, and was carried out at one field site during the spring, and at a different field site during the summer (Table 1).

Canopy reflectance spectra (350–2500 nm) were collected using a backpack spectroradiometer (ASD FieldSpec 4, Analytical Spectral Devices, Inc., Boulder, CO) with 1-nm spectral resolution at each sampling date prior to destructive sampling. All reflectance data were collected between 10:00 and 14:00. Conditions were overcast during six of the 16 sampling events in 2014; otherwise, conditions were clear and sunny during the remaining events in 2014 and during all sampling events in 2015. Fifteen reflectance readings were collected from each plot with the fiber optic cable (12.5° viewing aperture) oriented at 90° (nadir) approximately 1.0 m above the canopy to sample a 0.2-m diameter viewing area with each reading. The instrument was optimized and calibrated using a barium sulfate white reference at approximately 5-min intervals throughout each sampling event. Solar irradiance at the time of calibration was assumed to be representative of irradiance during the subsequent canopy reflectance readings during each interval. Reflectance spectra were used to identify novel indices based on the response variables, and to test a series of standard vegetative indices, selected to represent a range of spectral resolution requirements, number of wavebands, and intended applications (Table 2). Spectral indices of interest included the Normalized Difference Vegetation Index (NDVI), the Green Normalized Difference Vegetation Index (GNDVI), Red Edge Inflection Point (REIP), MERIS Terrestrial Chlorophyll Index (MTCI), Photochemical Reflectance Index (PRI), Chlorophyll Absorption Ratio Index (CARI), Normalized Difference Lignin Index (NDLI), and the Normalized Difference Nitrogen Index (NDNI). In addition to standard vegetative indices, analyses also included wavebands previously shown to be informative of herbage chemical composition in sainfoin (*Onobrychis sativa* Lam.) (Albayrak, 2008).

A single-beam LiDAR sensor (Lidar Lite, Pulsed Light Inc., Meridian, ID) was also used to remotely predict alfalfa canopy height prior to sampling in 2015. The LiDAR unit was mounted on a horizontal swinging arm attached to a tripod. The tripod was leveled at the edge of each plot with the arm extending over the plot at a constant height to measure distance from the sensor to the canopy (Fig. 1). Measurements were continuously recorded at a rate of 24 readings s^{-1} as the unit was manually moved across the center of each plot by rotating the arm at a constant rate, resulting in a minimum of 280 readings per plot. Predicted canopy height was calculated as the difference between LiDAR-estimated distance to the canopy and sensor height above the soil surface. Some plots with the greatest maturity had lodged at the time of sampling. Considering the intended application of this technology, these plots exceeded the practical range for harvest; therefore, LiDAR measurements from lodged plots were excluded from the analysis.

To quantify alfalfa maturity (MSW and MSC), a strip (7.6 cm × 3.0 m) was harvested from the center of each plot at 5.0-cm height using handheld electric clippers. Maturity samples were sorted according to the growth staging scale described by Kalu and Fick (1981). All stems within each growth stage were counted to calculate MSC, dried at 60 °C in a forced-air oven until constant mass, and weighed to calculate MSW. Bulk forage samples for measurement of yield and nutritive value were hand-harvested from 1.0 m^2 (four 0.25 m^2 areas) per plot, and dried at 60 °C in a forced-air oven until constant mass. Dry alfalfa biomass samples were ground to pass through a 6.0-mm screen using a Thomas Wiley Mill (Thomas Scientific, Swedesboro, NJ). The coarse ground samples were mixed, subsampled (30 g), and ground to pass through a 1.0-mm screen using a Cyclotec Sample Mill (FOSS North America, Eden Prairie, MN). Alfalfa subsamples were mixed thoroughly and scanned with a Perten NIRS (Model DA 7200, Perten Instruments, Springfield, IL) to estimate forage CP, NDF, and 48-h in-vitro NDFd according to equations calibrated with laboratory analyses.

2.2. Statistical analyses

Statistical analyses consisted of testing a group of previously published vegetative indices (Table 2), as well as the construction, validation, and comparison of new models to estimate alfalfa biomass, CP, NDF, and NDFd. Analyses were performed in the R statistical programming environment (R Development Core Team, 2017) using packages 'zoo' (Zeileis and Grothendieck, 2005) W. for data preprocessing and 'car' (Fox et al., 2017) for regression analyses. Only measurements collected under clear conditions with no obstruction from cloud cover (n = 254) were used for model construction and validation since the spectroradiometer used was a passive sensor. In practice, readings from active spectral sensors would not be affected by ambient light conditions.

Two methods were used to calculate cumulative GDUs. The first method ($GDU_{base\text{-}5}$) used a static base temperature (T_b) of 5 °C. The second method (GDU_{ALT}) used a modified scale informed by Sharratt et al. (1989) with T_b graduating continuously from 3.5 °C on 1 April to 10 °C on 31 July, then remaining at 10 °C throughout the remainder of the growing season. The cumulative GDU values used as model predictors and covariates were calculated for the specific growth period of each plot from the time of initial mowing to the time of sampling and harvest. Models were fit via linear regression to test both GDU calculations, MSW, and MSC as predictors of alfalfa biomass and nutritive value.

All canopy reflectance values were smoothed based on a moving average with 21-nm spacing, so that each value was replaced with the average reflectance of a 21-nm band centered on that wavelength. This served to smooth the spectral data and to simulate instrument outputs with spectral resolution that could feasibly be obtained with a UAV-compatible multi-spectral sensor. From the entire dataset, 60% of the

Table 2
Spectral vegetative indices screened as potential predictors of alfalfa yield and nutritive value.

Index	Abbreviation	Wavebands (nm)	Reference
Normalized Difference Vegetation Index	NDVI	650, 810	Rouse et al., 1973
Green Normalized Difference Vegetation Index	GNDVI	550, 810	Gitelson and Merzlyak, 1996
Red Edge Inflection Point	REIP	700†, 670, 780, 740	Guyot et al., 1988
MERIS Terrestrial Chlorophyll Index	MTCI	754, 709, 681	Dash and Curran, 2004
Chlorophyll Absorption Ratio Index	CARI	700, 500, 550, 670	Kim et al., 1994
Photochemical Reflectance Index	PRI	531, 570	Gamon et al., 1997
Normalized Difference Lignin Index	NDLI	1754, 1680	Serrano et al., 2002
Normalized Difference Nitrogen Index	NDNI	1510, 1680	Serrano et al., 2002
Wavebands for Sainfoin Forage Estimations	–	460, 550, 650, 780	Albayrak, 2008

† Waveband numbers represent 21-nm wavebands centered on the listed value.

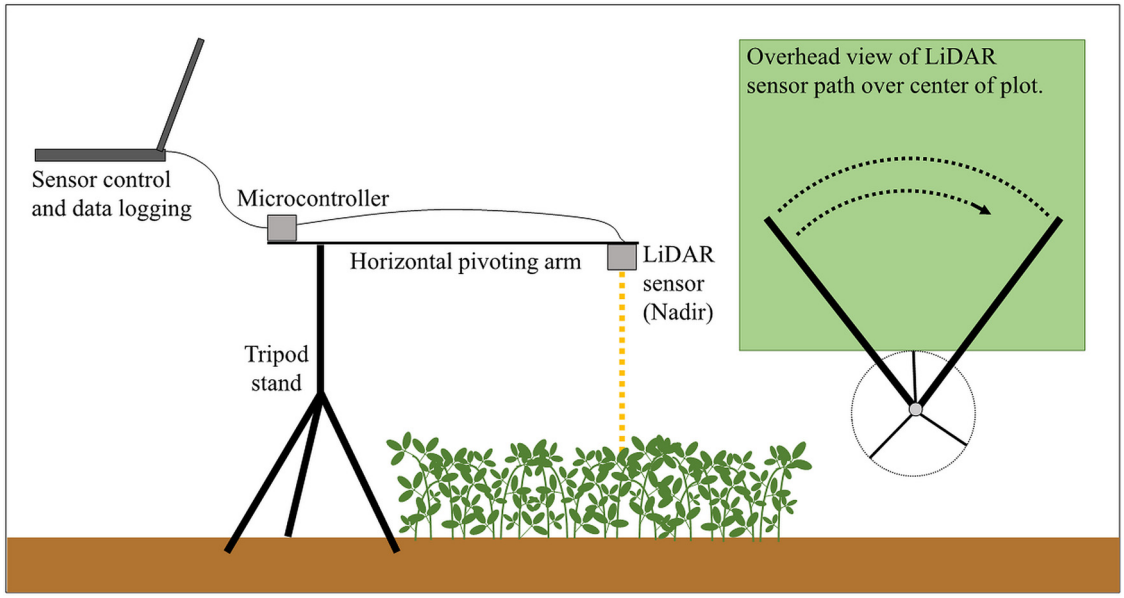

Fig. 1. Illustration of LiDAR sensor deployment to estimate canopy height in alfalfa plots.

data (n = 152) was sampled at random and stepwise regression was performed to identify the set of wavelengths as predictors that minimized the Bayesian information criterion (BIC) (Schwartz, 1978). This process was repeated 50 iterations, across which the average number of wavebands used ($\bar{\lambda}$) in the resulting models was determined. The most frequently occurring wavebands (n = $\bar{\lambda}$) in the selected models across the 50 iterations were retained as the final set of predictors for the corresponding dependent variable. This process was repeated for each dependent variable.

Canopy reflectance models were subsequently reduced by spectral range, limiting predictors to only wavebands within the visible and near-infrared spectrum (VIS-NIR; 400–1100 nm), and reiterating the step-wise procedure for each response (Table 3). The purpose of model reduction was to simplify the parameters required and improve utility and affordability of the application. Cumulative GDUs since the most recent harvest and LiDAR-estimated canopy height (2015) were also tested as covariates in the reduced VIS-NIR models (Fig. 2) to compare the prediction value of integrating different predictors and technologies. Only plots harvested prior to lodging in 2015 (n = 127) were used for development of models using LiDAR and for spectral models in comparison; therefore, these results are reported independently of the spectral models that were constructed and tested with both years of data.

A five-fold cross-validation procedure was applied to all predictive models for an objective comparison of remote- vs. temperature- vs. phenology-based predictions. The dataset was first divided into five random subsets. These subsets were held constant across all models per response variable. Next, during each of five iterations (or folds), a unique combination of four subsets were combined to calibrate a model for the predictors being tested. This model was then applied to predict the response variable values of the fifth subset. At the end of the five folds, the predicted values were correlated with the observed values to quantify the prediction accuracy of the model predictor(s) under testing for the corresponding dependent variable. The adjusted coefficient of determination was calculated for each of the resulting correlations to penalize model complexity and provide direct comparison of the various prediction methods.

Table 3
Canopy reflectance wavebands in the VIS-NIR region identified by stepwise variable selection to predict alfalfa yield, crude protein (CP), neutral detergent fiber (NDF), and neutral detergent fiber digestibility (48-h in-vitro) (NDFd).

Response	Predictive wavebands (nm)†
Yield	551, 711, 712, 1073, 1077, 1087
CP	351, 547, 549, 667, 706, 813, 1100
NDF	351, 461, 547, 549, 546, 820, 990
NDFd	351, 398, 520, 551, 677, 702, 704

†Reflectance values represent 21-nm wavebands centered on the listed value.

An additional model selection approach was used to identify a set of common wavebands, hereafter referred to as the utility spectra, in the VIS-NIR region to predict all response variables. All wavebands selected for the VIS-NIR models across all dependent variables were compiled and wavebands were evaluated for collinearity. When two or more wavebands were strongly correlated ($r > |0.95|$), the procedure removed the waveband(s) least correlated to the greatest number of response variables. This procedure resulted in a set of seven wavebands (6 VIS and 1 NIR) (Table 4). The utility spectra were subsequently combined with GDU predictors and LiDAR-estimated canopy height to test the hypothetical value of a single-integrated application.

3. Results

3.1. Environmental conditions

Monthly average air temperatures were similar (within 1 °C) to 30-yr averages during all alfalfa growth cycles in this study. The seasonal distribution of cumulative GDUs varied between the two GDU calculations tested (Table 5). The GDU_{ALT} values were greater at the beginning of the growing season and became increasingly less than $GDU_{base\text{-}5}$ values throughout the mid- and late-season months. During August 2014, the first month of the study, monthly total precipitation was 54% below normal; however, irrigation was applied to supply total water similar to monthly average precipitation. In 2015, total precipitation during the growing season exceeded the 30-yr average by 21% and no irrigation was applied.

3.2. Maturity-based predictions

The phenological indices, MSC, and MSW were generally accurate predictors of alfalfa CP, NDF, and NDFd relative to other measurements

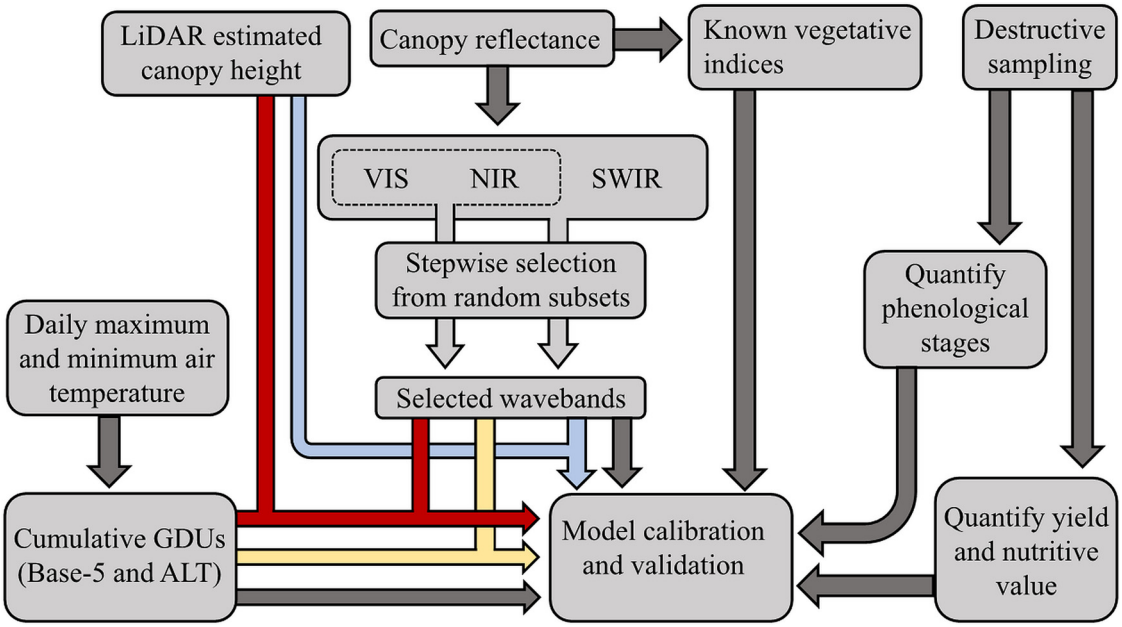

Fig. 2. Workflow diagram illustrating the sequences of data acquisition and processing for predictive model selection.

and models (Table 6). Predictions based on maturity explained 9–15% more variation in alfalfa yield and 20–42% more variation in NDFd than the best-performing models from temperature-based predictions and standard vegetative indices. Maturity-based predictions of alfalfa CP and NDF resulted in accuracies similar to GDU_{ALT} models, but greater accuracies than the standard vegetative indices tested. Both phenological indices were similar in prediction accuracy for all response variables.

3.3. Temperature-based predictions

The modified scale of GDU (GDU_{ALT}) base temperatures improved prediction accuracy for all dependent variables compared to the traditionally accepted static T_b of 5 °C (Table 6). Compared to $GDU_{base\text{-}5}$, estimations using GDU_{ALT} explained 17, 10, 9, and 14% more variation in yield, CP, NDF, and NDFd, respectively. Predictions of CP and NDF based on GDU_{ALT} resulted in prediction accuracies similar to or slightly greater than the maturity indices, but resulted in less accurate models for yield and NDFd (Table 6).

3.4. Canopy reflectance

Average values of NDVI increased rapidly from 0.74 at seven days of regrowth to 0.87 at 12 days of regrowth; then, all average NDVI measurements taken from 14 to 62 days of regrowth were within the range of 0.89–0.94. Of the indices tested, NDVI, SFI, PRI, NDLI, and NDNI explained less than 10% of the variation in any of the dependent variables; therefore, outputs of these indices are not reported in further

Table 5
Total Growing Degree Units according to two different calculations and total monthly precipitation from April to October in 2014 and 2015 at Rosemount, MN.

Month	GDU_{base-5} [a]		GDU_{ALT}		Precipitation	
	2014	2015	2014	2015	2014	2015
	°C		°C		mm	
April	68	133	78	150	158 (81) [b]	51 (−25)
May	279	279	251	252	117 (9)	114 (6)
June	454	443	377	366	268 (149)	135 (15)
July	489	512	359	382	74 (−41)	220 (105)
August	513	458	358	303	52 (−62)	126 (11)
September	343	411	197	261	70 (−17)	126 (39)
October	128	141	22	42	39 (−28)	63 (−4)

[a] GDU_{ALT}, cumulative growing degree units since last alfalfa harvest, base temperature graduating from 3.5 °C (1 April) to 10 °C (31 July) and static at 10 °C through the remainder of the year; $GDU_{base\text{-}5}$, cumulative growing degree units since last alfalfa harvest (base temperature = 5 °C).
[b] Departures from 30-yr averages shown in parentheses.

Table 4
Matrix of correlation coefficients between alfalfa yield, nutritive value, and canopy reflectance wavebands (the UTILITY spectra) selected for predictive models.

	Response				Canopy reflectance waveband (nm)						
	Yield	CP	NDF	NDFd	351	398	461	551	667	712	1077
Yield	1.00	–	–	–	–	–	–	–	–	–	–
CP	−0.82	1.00	–	–	–	–	–	–	–	–	–
NDF	0.79	−0.97	1.00	–	–	–	–	–	–	–	–
NDFd	−0.81	0.88	−0.84	1.00	–	–	–	–	–	–	–
351	−0.18	0.21	−0.30	0.10	1.00	–	–	–	–	–	–
398	−0.46	0.47	−0.46	0.48	0.72	1.00	–	–	–	–	–
461	−0.11	0.11	−0.06	0.11	0.51	0.79	1.00	–	–	–	–
551	−0.68	0.74	−0.71	0.70	0.42	0.80	0.58	1.00	–	–	–
667	0.18	−0.16	0.20	−0.21	0.30	0.45	0.86	0.24	1.00	–	–
712	−0.35	0.45	−0.45	0.40	0.50	0.78	0.75	0.87	0.50	1.00	–
1077	0.36	−0.22	0.14	−0.17	0.33	0.22	0.23	0.09	0.09	0.46	1.00

Table 6
Adjusted coefficients of determination (R^2) from 5-fold model validation procedure and number of wavebands used (λ) in models to predict alfalfa yield (kg DM ha^{-1}), crude protein (CP), neutral detergent fiber (NDF), and neutral detergent fiber digestibility (48-h in-vitro) (NDFd).

Model	Yield		CP		NDF		NDFd	
	R^2	λ	R^2	λ	R^2	λ	R^2	λ
MSC†	0.67	–	0.84	–	0.83	–	0.74	–
MSW	0.65	–	0.83	–	0.82	–	0.77	–
GDU $_{base-5}$	0.39	–	0.75	–	0.74	–	0.43	–
GDU $_{ALT}$	0.56	–	0.85	–	0.83	–	0.57	–
MTCI	0.32	3	0.15	3	0.07	3	0.13	3
GNDVI	0.52	2	0.40	2	0.27	2	0.35	2
REIP	0.45	4	0.24	4	0.15	4	0.21	4
CARI	0.09	4	0.14	4	0.15	4	0.07	4
Albayrak 2008 bands	0.78	4	0.72	4	0.66	4	0.70	4
VIS + NIR + SWIR	0.78	6	0.81	8	0.69	9	0.78	7
VIS + NIR	0.81	6	0.78	7	0.70	7	0.76	7
(VIS + NIR) + GDU$_{ALT}$	0.85	6	0.91	7	0.87	7	0.83	7
UTILITY	0.78	7	0.73	7	0.72	7	0.70	7
UTILITY + GDU$_{ALT}$	0.81	7	0.90	7	0.88	7	0.82	7

† See Abbreviations section for definitions.

comparisons. Among the remaining indices, models based on GNDVI resulted in the most accurate predictions for all dependent variables, followed by REIP (Table 2). Both GNDVI and REIP resulted in more accurate predictions of yield than models based on GDUs alone. Otherwise, previously established indices, including MTCI and CARI, resulted in less accurate predictions for all dependent variables compared to all reported methods of estimation. Models using the four wavebands reported by Albayrak (2008) for estimating nutritive value in sainfoin (Table 2) resulted in prediction accuracies similar to models selected from the VIS-NIR-SWIR for yield and NDF, but lower accuracy for CP and NDFd (Table 6).

Models using the full spectral range (VIS-NIR-SWIR) had prediction accuracies similar to models using only the VIS-NIR for all response variables (Table 6). Optimum spectra from the VIS-NIR-SWIR range included one and two more wavebands than the VIS-NIR models for CP and NDF, respectively, and the number of selected wavebands was the same across models for both yield and NDFd. Models from both spectral ranges had greater prediction accuracy for yield than models based on maturity, air temperature, or vegetative indices; however, predictions of nutritive value parameters were similar to or less accurate than maturity-based predictions. The utility spectra, seven common wavebands centered on 351, 398, 461, 551, 667, 712, and 1077 nm, resulted in prediction accuracy similar to the VIS-NIR models for NDF, although accuracy was reduced modestly for yield, CP, and NDFd.

3.5. Combined models

Predictions combining GDU$_{ALT}$ with selected wavebands in the VIS-NIR region had greater accuracy for all dependent variables than models based solely on contact measurement of maturity, temperature-based estimations, or canopy reflectance alone (Table 6). The UTILITY spectra combined with GDU$_{ALT}$ resulted in similar accuracies to VIS-NIR + GDU$_{ALT}$ models for the nutritritive value parameters and slightly reduced accuracy for yield. In plots sampled before lodging with corresponding LiDAR measurements (n = 127), yield estimations based on LiDAR-estimated canopy height were strongly correlated with alfalfa biomass (R^2 = 0.85; y = 0.9474x + 226.6). The addition of LiDAR-estimated canopy height improved predictions of yield, NDF, and NDFd compared to VIS-NIR models alone (Table 7). Adding LiDAR to the VIS-NIR-GDU$_{ALT}$ models improved predictions of yield; however, it did not improve prediction accuracy for the nutritive value parameters. Using only the seven utility wavebands, GDU$_{ALT,}$ and LiDAR-estimated canopy height, prediction accuracies were similar to models integrating GDU$_{ALT}$ and LiDAR with the response-specific VIS-NIR wavebands.

Table 7
Adjusted coefficients of determination (R^2) from 5-fold model validation procedure and number of wavebands used (λ) in models based on canopy reflectance, cumulative GDUs, and LiDAR-estimated canopy height to predict alfalfa yield (kg DM ha^{-1}), crude protein (CP), neutral detergent fiber (NDF), and neutral detergent fiber digestibility (48-h in-vitro) (NDFd).

Model	Yield		CP		NDF		NDFd	
	R^2	λ	R^2	λ	R^2	λ	R^2	λ
VIS + NIR†	0.79	6	0.66	7	0.60	7	0.67	7
(VIS + NIR) + GDU$_{ALT}$	0.79	6	0.87	7	0.76	7	0.86	7
(VIS + NIR) + LiDAR	0.84	6	0.66	7	0.62	7	0.72	7
(VIS + NIR) + LiDAR + GDU $_{ALT}$	0.84	6	0.86	7	0.76	7	0.86	7
UTILITY + GDU $_{ALT}$	0.78	7	0.86	7	0.75	7	0.86	7
UTILITY + GDU $_{ALT}$ + LiDAR	0.84	7	0.86	7	0.76	7	0.86	7

† See Abbreviations section for definitions.

4. Discussion

The findings of this study demonstrate potential for improved estimations of alfalfa yield and nutritive value based on remote sensing measurements, and also support the usefulness of estimations based on morphology or air temperature. Maturity-based predictions were relatively informative, although prediction accuracies were less than described by Kalu and Fick (1983), who reported R^2 values of 0.88 and 0.95 for CP and NDF, respectively. The greatest discrepancy was in predictions of NDF, where the optimum maturity-based predictions in this study explained 12% less of the variation in NDF compared to Kalu and Fick (1983). Previous work has not reported methods of estimating alfalfa NDFd in situ; however, maturity-based predictions of NDFd were also less accurate than expected, as Kalu and Fick (1983) found strong correlations with fiber fractions related to NDFd, including ADF and lignin. A range of factors could have contributed to these inconsistencies, including differences between alfalfa cultivars and environmental conditions (Buxton, 1996), providing further justification for specialized and integrated models that account for environmental factors.

Improved predictions based on GDU$_{ALT}$ compared to GDU$_{base-5}$ support the findings of Sharratt et al. (1989) and warrant further investigation into the use of temporally-graduating base temperatures in GDU calculations for alfalfa. Both models based on cumulative GDUs had greater accuracy than reported by Hakl et al. (2010) for CP and NDF (R^2 = 0.65 and 0.40, respectively). However, Hakl et al. (2010) likely constructed models using a narrower range of responses with greater environmental variability compared to the current study, as they compiled data across 4 yr and only harvested from the late-vegetative to early-bloom growth-stages. Poor prediction accuracy of NDFd using GDUs supports Sulc et al. (1999), who concluded that in-field estimations of alfalfa nutritive value should not be based on GDUs alone. As water was not a limiting factor for alfalfa growth in this study, cumulative precipitation was collinear with cumulative GDUs and did not provide additional insight to the factors affecting alfalfa growth. Under conditions of limited water, using cumulative precipitation as a covariate would be expected to improve model predictions since this factor would influence plant growth independently of temperature.

The screening of vegetative indices generally demonstrates the need for specialized models to predict alfalfa yield and nutritive value, as most indices explained little to no variation in the dependent variables. One exception was GNDVI, which was relatively informative compared to other spectral indices, and only required two wavebands, meaning it would be one of the most affordable spectral indices to measure. The usefulness of the wavebands correlated with sainfoin forage nutritive value indicates potential for transferability of this technology across forage species, although Albayrak (2008) reported greater accuracy of

individual wavebands and simple indices than observed in this study. For example, they found that the NIR:RED ratio, using the same spectral information as NDVI, explained 61–80% of the variation in most forage nutritive value parameters, whereas NDVI explained < 10% of variation in all parameters in this study.

Predictions of CP based on seven wavebands in the VIS-NIR spectral range were similar to those achieved by Starks et al. (2016), who used this range at higher resolution to estimate CP (R^2 = 0.78). However, VIS-NIR-based predictions of NDF in this study were less accurate (R^2 = 0.69) than reported by Starks et al. (R^2 = 0.77). This supports the hypothesis that fewer wavebands with lower spectral resolution may be used to inform predictions of alfalfa nutritive value, although the greatest accuracy may be obtained with higher spectral resolution. Similarly, predictions of yield based on canopy reflectance alone were greater than those reported by Pittman et al. (2015) (R^2 = 0.38–0.56), yet a wider spectral range with greater resolution was selected for the current study.

The demonstrated potential for LiDAR-estimated canopy height to predict alfalfa biomass agrees with other alfalfa yield predictions based on height (Pittman et al., 2015; Lyons et al., 2016) and adds value to the potential for remote sensing applications in alfalfa management. One challenge is LiDAR-based estimations rely on a precise, known sensor-height above the ground surface. The efficacy of using LiDAR measurements before and after alfalfa growth would subsequently depend on the accuracy of the UAV altimeter, or the ability of sensors to estimate the distance to the ground through the alfalfa canopy. In a field application, structure-from-motion analyses from UAV imagery, before and after alfalfa growth, may be a more efficient way to remotely estimate canopy height (Matthews and Jensen, 2013). Aerial imagery from UAVs can be used to render 3-D models referenced to fixed-height ground control points, which would likely optimize both affordability and accuracy of non-contact estimations of alfalfa canopy height. The improved fit of combined models supports the hypothesis that integrating non-contact measurements with environmental information can provide more reliable predictions than using these methods alone. Owens et al. (1995) reported improved estimations of fiber composition using measurements of the tallest stem in sample. This aligns with the improved predictions of NDF and NDFd when LiDAR-estimated canopy height was included in the VIS-NIR models.

The overall improvement of models integrating GDUs with canopy reflectance establishes a valuable concept that can be easily incorporated into future applications of remote sensing in agriculture. In this study, measurement of the seven utility wavebands, integrated with cumulative GDUs on the modified scale, provided near-optimum predictions relative to other approaches. Including a remote estimate of canopy height in the completely integrated model was ultimately beneficial for only yield predictions; however, this information can easily be obtained through analyses of digital imagery if a UAV is already being used to collect measurements of canopy reflectance. Therefore, a practical and valuable application of remote sensing technology could be a UAV carrying a multi-spectral sensor measuring the seven utility wavebands as well as an RGB digital camera. All spectral data and imagery could be analyzed, real-time, with environmental data to estimate current properties of the crop and forecast optimum harvest time.

5. Conclusions

This work establishes potential for integrating environmental data such as GDUs with canopy reflectance data and remote measurements of canopy height for improved estimations of alfalfa yield and nutritive value. These methods could be applied on-farm across large acreages and multiple fields to inform economically efficient decisions regarding timing of harvest, which field(s) to harvest first, or how to ration the current feed supply relative to the anticipated harvest time, yield, and nutritive value. Farm-specific models may be developed and continuously improved by monitoring predictors alongside yield and quality parameters at each harvest. Modern software applications can easily retrieve environmental data such as estimated soil type, temperature, rainfall, and relative humidity based on geographic location, and could apply iterative regression with every harvest to improve predictive models. The increasing spectral and temporal resolution, and availability of satellite-measured spectral data may also facilitate rapid assessment of crop status across large geographic regions to inform market predictions and management decisions. As remote sensing and predictive crop modeling technologies continue to be developed and applied across the landscape, the overall resource-use efficiencies of agricultural industries will be improved for greater profitability and system resilience.

Acknowledgements

This research was supported by the University of Minnesota Agricultural Experiment Station. We appreciate the technical contributions of Joshua Larson, Eric Ristau, Zach Marston, and Alexander Hummel.

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