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ORIGINAL RESEARCH

Estimation of the nutritive value of grasslands with the Yara N-sensor field spectrometer

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Abstract

Forage crops are a cornerstone of the agricultural industry in Nordic countries. Economic and ecological performances are directly linked to adapted farming practices, which require timed and precise information on the nutritive value of the forage. Field spectrometers could offer an interesting alternative to time-consuming laboratory measurements, as they provide near real time information. We used a handheld version of a field spectrometer already commercialized for cereal adjustable rate fertilization, to evaluate its potential for grassland nutritive quality estimation. Spectral data and samples were acquired over experimental fields and plots in four locations in Northern Sweden; samples were analyzed using wet chemistry to determine the crude protein concentration, the in vitro true digestibility, the neutral detergent fiber and the neutral detergent fiber digestibility. Grid-based adjusted spectral indices, partial least squares, random forest and support vector machine were tested to link the spectral data to the nutritive traits. Partial least squares and support vector machine outperformed the adjusted spectral indices and random forest. Best predictions were obtained with partial least squares for in vitro true digestibility and neutral detergent fiber (R^2 of 0.64 and 0.78 and normalized root mean square error [nRMSE] of 2.1 and 8.0%, respectively) and with support vector machine for crude protein and neutral detergent fiber digestibility (R^2 of 0.49 and 0.65 and nRMSE of 13.0 and 3.8%, respectively). These results suggests that there is a potential for this affordable, industry-ready spectrometer to be used as a practical farming tool, although more comprehensive datasets are needed to ensure that robust models are developed.

1 | INTRODUCTION

Forage crops are of high importance in food production systems, especially for the dairy and meat sectors. In the Nordic countries, leys (harvested grasslands as part of a crop rotation) are a very important part of the agricultural landscape and can represent up to 70% of the land use (Jordbruksverket, 2019) as, for example, in Northern Sweden. Quantity and quality of produced forage have a direct influence on the economic and ecological performances of the meat and dairy

Abbreviations: CP, crude protein; DM^{-1}, per dry matter; IVTD, in vitro true digestibility; MR, multivariate regression models; NDF, neutral detergent fiber; NDFD, neutral detergent fiber digestibility; NDI, normalized difference quality indices; NIR, near infrared; PLS, partial least squares; PLSR, partial least squares regression; RF, random forest; RMSE, root mean square error; SRI, simple ratio quality indices; SVM, support vector machine; YNS, Yara N-sensor.

production industries. Forages with low protein or energy concentrations require the use of concentrates to maintain the productivity, and low harvest yield needs to be compensated for by purchasing extra feed.

Farmers largely rely on laboratory-based estimations of nutritive value, such as wet chemistry or near infrared (NIR) spectrometry. Although providing robust and accurate results, laboratory analysis is time-consuming, as it can take from several days to weeks for the farmer to obtain results. Solutions that would allow a near real time estimation of the digestibility would be more adapted to the needs of farmers, who need an almost immediate response to efficiently schedule their harvest.

In recent years, field spectrometers have become increasingly used in both research and industry. These sensors deliver rich spectral information, usually encompassing the visible and NIR parts of the light spectrum. In the case of crops, field spectrometers measure the plant-reflected light, which is directly linked with the physical and chemical properties of the canopy. This link can further be utilized using appropriate mathematical approaches, such as inversion of radiative transfer models, machine learning, or simple regression based on vegetation indices.

From the grassland perspective, Darvishzadeh et al. (2008) performed an inversion of PROSAIL on data obtained from a GER 3700 spectroradiometer to estimate leaf area index and canopy chlorophyll content in heterogeneous grasslands in Italy. They concluded that this approach performs with satisfactory accuracy, although the performance is largely dependent on the heterogeneousness of the sward composition. Zhou et al. (2019) used a multivariate regression-based approach and performed a comparison of support vector machines (SVMs) and partial least squares (PLS) regression to link Yara N-sensor (YNS) spectral data with crude protein (CP) concentration, dry matter yield, and nitrogen (N) uptake of leys in Northern Sweden. Their results showed that both modelling approaches provided satisfactory results, yet SVM-based models tended to outperform PLS. Fava et al. (2009) performed an exhaustive grid search to compute adjusted vegetation indices using spectral data acquired from an ASD Fieldspec HandHeld spectroradiometer over Mediterranean grasslands to estimate fresh biomass, leaf area index, N content, and N concentration. They concluded that adjusted, narrow-band vegetation indices perform significantly better than traditional vegetation indices such as the normalized difference vegetation index and other broad band indices. Other examples of applications of spectroradiometers for temperate grassland monitoring can be found in Wachendorf et al. (2018), with all studies concluding that field spectrometers can be used to assess agronomic performances of grasslands.

It is worth noting that most of the studies that evaluated field spectrometers to retrieve nutrition quality or the yield of grasslands used research-grade field spectrometers, such as the FieldSpec 4 (ASD Inc.). These instruments provide data with a large number of narrow spectral bands (usually several hundreds) that cover the visible, NIR, and short-wave infrared spectral ranges and provide a comprehensive view of the spectral characteristics of plants. However, they require specific knowledge on spectral measurements and processing. This, and their elevated cost, makes them unsuitable for developing ready-to-use solutions for farmers. Industry-grade field spectrometers, on the other hand, usually explore a more restricted spectral range (including the visible and part of the NIR ranges) with coarser spectral resolution and less spectral bands. However, their design makes them relatively easy to use and more affordable for private end users. The YNS is an already commercialized field spectrometer mounted on tractors and primarily used to evaluate the N needs of cereal crops. As of 2019, there were 1,000 YNS units used in Europe, of which 280 are used in the Nordic countries (K. Nissen, personal communication, 27 May 2021). As this sensor is already used by farmers, there is potential for a relatively easy implementation of YNS-based solutions for ley management.

As mentioned earlier, different mathematical approaches used to link spectral information with plant traits have shown various accuracy and robustness performances, depending on the agronomic and environmental contexts. Here we focused on the use of three multivariate regression models (MR; PLS, random forest [RF], and SVM) and on a spectral index-based approach for estimating forage qualitative traits. The reason why the inversion of radiative transfer models was not tested is that the absence of spectral information in the short-wave infrared range drastically limited the possibility to take full advantage of this approach.

Spectral indices have the advantage of simplicity, as they only involve a small number of spectral bands, which carry most of the information linked to the variability of vegetation traits. Although many vegetation indices have been developed to monitor the biomass accumulation of vegetation or the chlorophyll content of a canopy (e.g., Boegh et al.,

Core Ideas

- A commercial spectrometer, used for cereal fertilization, has been tested for on-field forage quality estimation.
- Reflectance spectra were matched against lab measurements using several multivariate regression models.
- Partial least squares and support vector machine showed best performances.
- The tested field spectrometer has good potential for practical applications with grasslands.

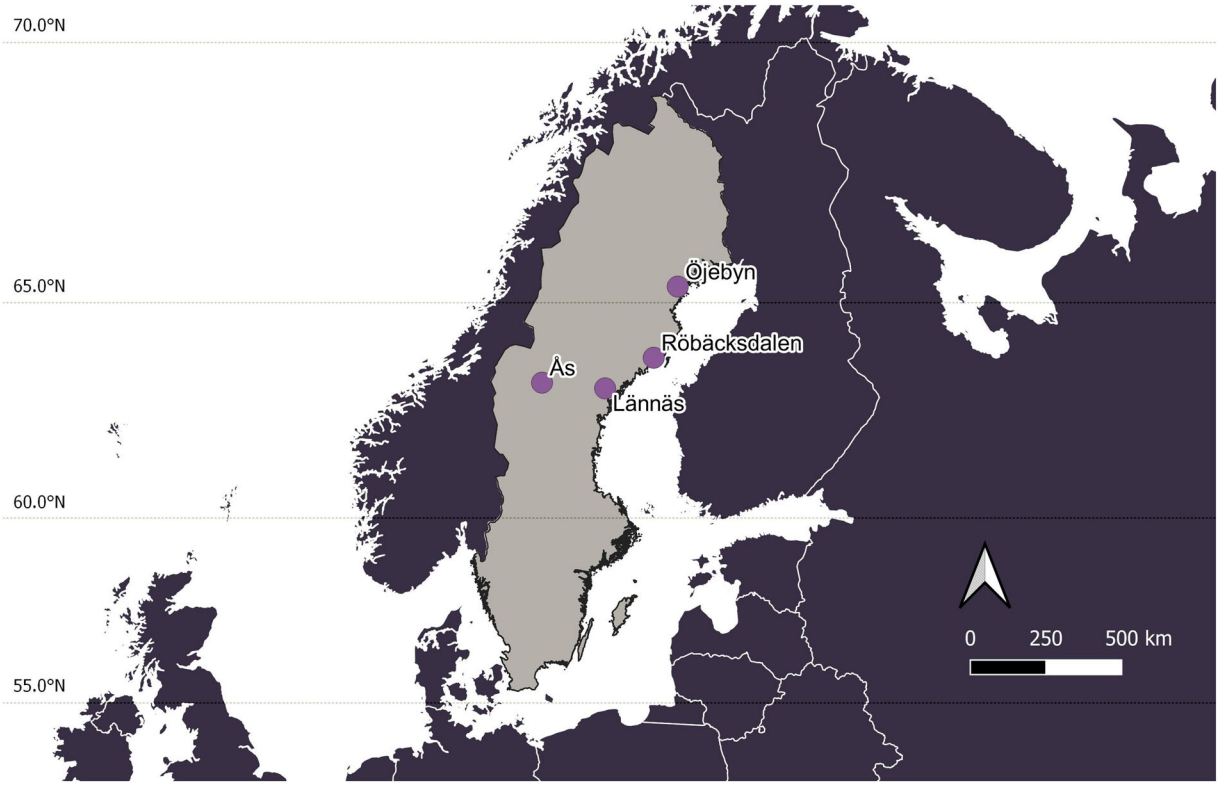

FIGURE 1 Sites used in the study

2012; Clevers & Gitelson, 2013; Tucker, 1979), to the best of our knowledge there is no vegetation index specific for forage qualitative assessment of vegetation. A grid-based search of optimal combinations of spectral bands into a vegetation index, similar to what was proposed by Thenkabail et al. (2000) could lead to quality-specific indices that could further be used to develop simplified (i.e., with only a few narrow spectral bands), more affordable sensors.

Therefore, the objective of this paper is to evaluate the performances of PLS, RF, SVM, and spectral indices for the estimation of forage nutritive value traits (including CP, in vitro true digestibility [IVTD], neutral detergent fiber [NDF], and neutral detergent fiber digestibility [NDFD]) from field data obtained from a hand-held version of the YNS.

2 | MATERIALS AND METHODS

Agronomic and spectral data were acquired between 2017 and 2019 on experimental plots and production fields with mixtures of grass (timothy; *Phleum pratense* L.) and legume (red clover; *Trifolium pratense* L.) at four sites in Northern Sweden (Figure 1). Samples were taken from both experimental plots and production fields, with a range of harvest times (1st, 2nd, and 3rd harvest), compositions (grass and clover), and fertilizer management practices (organic and mineral), overall representing a diverse dataset typical of ley management in Northern Sweden. Nitrogen fertilizer rates are not presented, because the N supply from organic amendments preceding the ley is difficult to assess, and the amount of mineral N applied for different harvests is not directly comparable.

As the objective of this research was to develop a system to help farmers to decide on when to harvest, samples were collected over many days around the actual harvest date to obtain a range of forage qualities. A 76-cm diameter hoop was used to delineate the samples for both spectral measurements and harvest. In total, 336 samples were acquired and used in this study.

2.1 | Spectral data

The YNS captures the canopy-reflected light in 60 discrete bands ranging from 400 to 1,000 nm. The commercial version of the YNS is tractor-mounted. In this study, we used a hand-held version that includes (a) an incoming light sensor used to measure the incoming radiant flux and (b) the reflected light sensor, which has a 25° field of view.

All measurements were taken using a zenithal viewing angle of 45° on clear sky days and close to the solar noon to ensure comparability of results. Measurements were taken with a 90° azimuthal angle with respect to the sun. This choice was motivated by the fact that, to be suitable for practical farming applications, the measurement should as simple and rapid as possible. Using the incoming light information, canopy-reflected light was converted

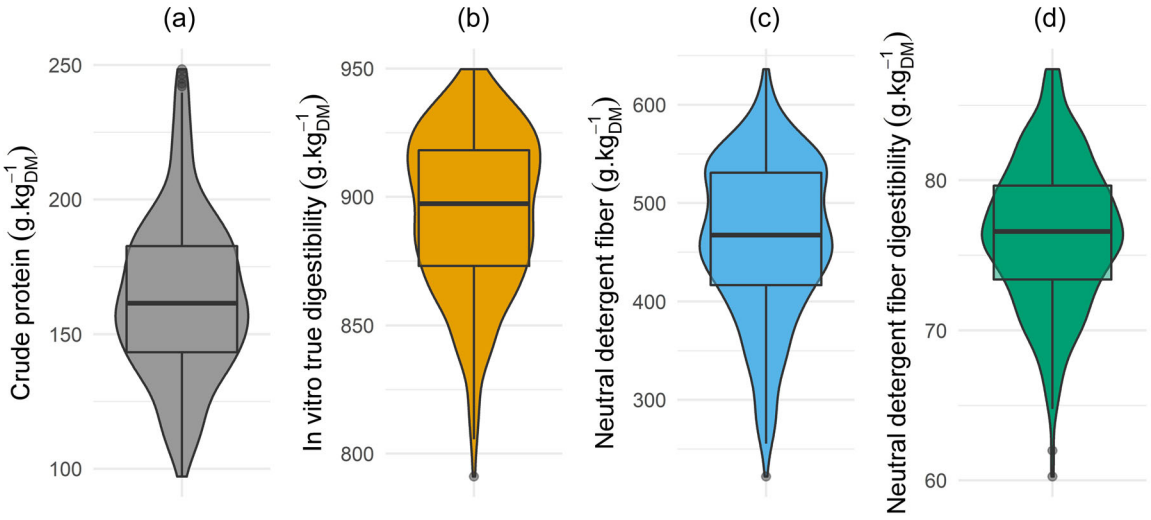

FIGURE 2 Violin plots and boxplots of the distribution of the values of the crude protein (a), in vitro true digestibility (b), neutral detergent fiber (c), and neutral detergent fiber digestibility (d) concentrations

to hemispherical-conical reflectance factor, as defined by Schaepman-Strub et al. (2006). Resulting canopy reflectance information was used for developing vegetation indices-based and multivariate regression-based models.

2.2 | Agronomic data

Once spectral data were acquired, vegetation samples were harvested at 7 cm above ground, stored in cool boxes and taken back to the laboratory for hand separation of grass and legume fractions and drying (at 60 ˚C until weight stabilizes, approximately 48 h). Dried samples were then ground, passed through a 1-mm sieve and analyzed for nutritive value using wet chemistry. In vitro true digestibility and NDFD were determined using subsamples incubated in F57 ANKOM digestion bags at 39 ˚C for 48 h following a modified ANKOM procedure (Valentine et al., 2019) with a Daisy II 200/220 incubator (ANKOM Technology). Neutral detergent fiber was obtained from subsamples using sodium-dodecyl-sulfate in the ANKOM system as proposed by Van Soest et al. (1991). Nitrogen was analyzed with a Leco FP-528 N analyzer (Leco Corp.) using the methodology proposed in Helrich (1990). Crude protein was determined by applying a 6.25 factor to the measured N. Crude protein, IVTD, and NDF are reported as fractions of dry matter, whereas NDFD is reported as a fraction of NDF.

2.3 | Adjusted spectral indices-based regression models

Adjusted spectral indices computed from the YNS data were used to estimate IVTD, NDF, and NDFD. We used two types of spectral indices: simple ratios and normalized differences.

Simple ratios are formalized as follows

$$\text{SRI} = \frac{R_{b1}}{R_{b2}}$$

where SRI is simple ratio quality indices, and R_{b1} and R_{b2} are the reflectance from two spectral bands of the sensor.

Normalized difference quality indices (NDI) were calculated using the following formula:

$$\text{NDI} = \frac{\left(R_{b1} - R_{b2}\right)}{\left(R_{b1} + R_{b2}\right)}$$

To define the optimal wavebands for each qualitative variable-specific ND, a grid search was performed by exhaustively combining the 60 available spectral bands, similarly to what was done by, for example, Inoue et al. (2012), Jay, Gorretta, et al. (2017), and Thenkabail et al. (2000). Each band combination was used to build a linear regression with each trait of interest and evaluate the capability of the adjusted spectral index to account for changes in quality.

2.4 | MR

Multivariate regression models are versatile mathematical tools that account for the influence of several explanatory variables on a given response variable. Many types of models exist, with various framework assumptions, mechanisms, and so on, which means that different models can yield different performances when estimating the value of an agronomic trait based on spectral data. In this study, three types of models were assessed: partial least square regression, SVM, and RF.

Partial least squares regression (PLSR) is a prominent multivariate data analysis method, which can effectively deal with multicollinearity among explanatory variables. Several latent variables can be extracted to replace original explanatory variables for eliminating redundant information. Partial least squares regression has great prediction ability, especially when the number of samples is less than the number of explanatory variables. The principle of PLSR is described in Geladi and Kowalski (1986). The pls package (Liland et al., 2021) available in R (R Core Team, 2020) was used in this study. Models were adjusted using the *plsr* function, which automatically performs a mean-centering of the data for better results. For each iteration, an optimal number of latent variables was selected to reduce the risk of overfit. Root mean square error (RMSE) was used as a cost function to evaluate the performances of every iteratively adjusted PLS as a function of the number of latent variables. The optimal number of latent variables was determined based on the slope of the RMSE and considered to be reached when the slope value became superior to −0.2.

Random forests is a widely used machine learning tree-based method that was introduced by Leo Breiman in the early 2000s (Breiman, 2001). It basically works considering a given number of decision trees and nodes randomly constructed through the explanatory variables. As such, they do not rely on Euclidean Distance and do not require any mean-centering of data. In this study, RF algorithms was also implemented in R software (R Core Team, 2020), using the randomForest package (Liaw & Wiener, 2002). Here we built a RF model based on 150 trees, because there is still not a consensus on how to choose the initial number of trees (Speiser et al., 2019).

Since their development by Vapnik (1982), SVM have become largely used for various classification and regression tasks. The reader is referred to Cristianini and Shawe-Taylor (2000) for a detailed presentation of the theory of SVM. Here, we used the liquidSVM package (Steinwart & Thomann, 2017) in R software (R Core Team, 2020). This package was chosen (a) because of its efficiency with the time of computation and (b) because of its automated grid search for C and γ hyperparameters selection. The *svm* function of liquidSVM automatically performs a scaling of the data to improve its accuracy.

For each variable of interest and regression approach, an iterative ($n = 100$) calibration and validation approach was used. For each iteration, the calibration step was performed by randomly selecting two-thirds of the complete dataset and using the remaining third for validating the performances. The purpose of the randomized iterative process was to evaluate the robustness of each approach by taking full advantage of the available dataset, which represents different managements, years, locations, and harvests, hence providing a representative case-study of ley farming in Northern Sweden. This iterative process also results in a range of potential accuracies rather than an individual value as obtained from the traditional individual calibration/validation approach. The iterative approach used here allows to compare distributions of accuracies and detect potential overfit and outliers. Model performances were evaluated for both calibration and validation using three metrics: the coefficient of determination (R^2), RMSE, and the nRMSE.

Codes used for calibrating and testing the models are available from the authors on request.

3 | RESULTS AND DISCUSSION

The distributions and quartiles of the different quality variables are summarized in Figure 2. The CP concentration of the samples had minimum and maximum values of 97 and 248 g kg per dry matter (DM^{-1}), respectively, with an average value of 164 g kg DM^{-1}.

The IVTD ranged between 791 to 950 g kg DM^{-1}, with a mean value of 894 g kg DM^{-1}. The NDF ranged between 222 and 636 g kg DM^{-1} (mean value of 462 g kg DM^{-1}). The NDF digestibility ranged between 60 and 87 g kg DM^{-1} with a mean value of 76 g kg DM^{-1}.

Figure 3 shows the average and standard deviation values of every canopy spectrum acquired in this study.

The spectra show low reflectance in the visible range (400–700 nm) with a slight increase around the green region (550 nm), related to the canopy chlorophyll content. A sharp increase in reflectance is observed in the red edge region (around 700 nm), followed by a stabilization around 0.6 reflectance factor in the NIR range (750– 925 nm) and a concave shape around 950 nm linked to the canopy water content (Peñuelas et al., 1993).

The results of adjusted simple ratio quality indices (SRIs) for each quality variable are presented in Figure 4. Note that NDI results were very similar to the ones obtained for SRIs and are thus not presented here. The most important spectral regions change depending on the assessed quality variable, but the overall results show low R^2 and *RMSE* values for every variable (Table 1).

For CP, the visible region carried most of the information, especially the blue and green regions, although the best combination was obtained for the blue region only (410 and 430 nm, $R^2 = 0.24$). For IVTD, the green, red-edge, and near-infrared regions carried most information, the best combination including the 760 and 800 nm bands, with an R^2 of 0.40. The results obtained for NDF show similar trends as for IVTD, although the importance of the red-edge and near-infrared regions increased compared with IVTD, whereas the importance of the visible region decreased. The best combination was obtained for 750 and 790 nm bands and R^2 of 0.50. For NDFD, the most important regions were located in the

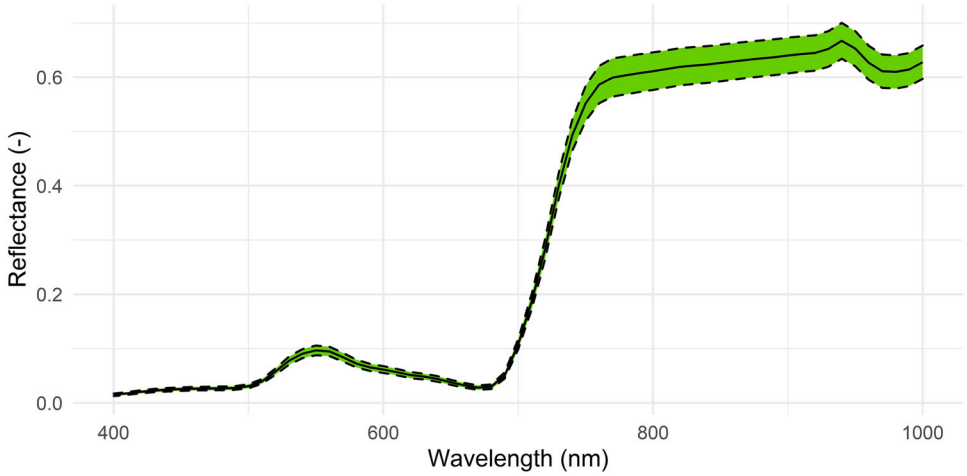

FIGURE 3 Average (full line) and standard deviation (dashed lines) of the spectra acquired in the study

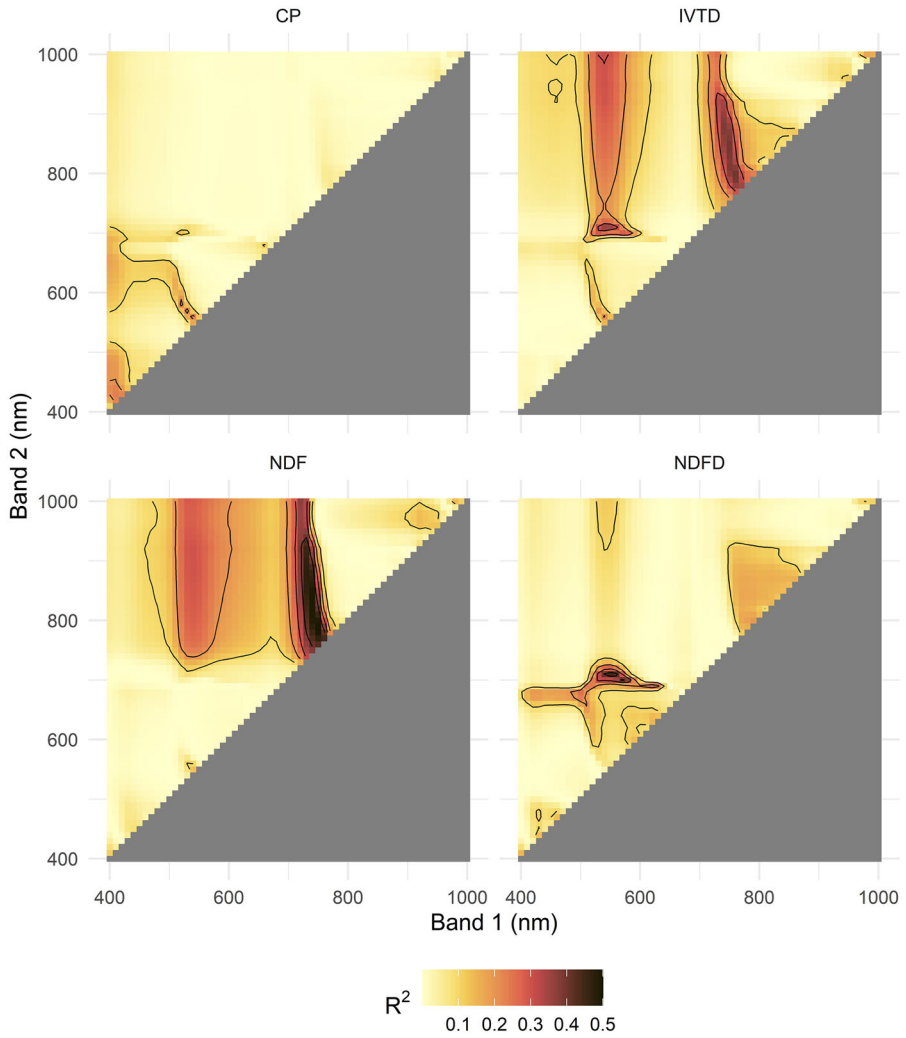

FIGURE 4 Heatmaps of the coefficient of determination (R^2) of simple ratio quality indices for estimations of crude protein (CP), in vitro true digestibility (IVTD), neutral detergent fiber (NDF), and neutral detergent fiber digestibility (NDFD) for every combination of bands. All values are averages of the 100 models built during the iterative calibration/validation process

TABLE 1 Comparison of the performances of the different models

Variable	Model	R^2	RMSE	nRMSE
CP (g kg DM^{-1})	PLS	0.49	21.4	13.0
	RF	0.24	26.0	15.9
	SRI	0.24	25.7	15.7
	SVM	0.49	21.3	13.0
IVTD (g kg DM^{-1})	PLS	0.64	18.6	2.1
	RF	0.41	23.6	2.6
	SRI	0.40	23S.9	2.7
	SVM	0.63	18.8	2.1
NDF (g kg DM^{-1})	PLS	0.78	37.1	8.0
	RF	0.48	56.8	12.3
	SRI	0.50	55.6	12.0
	SVM	0.76	39.1	8.5
NDFD (g kg DM^{-1})	PLS	0.58	3.1	4.1
	RF	0.37	3.8	5.0
	SRI	0.44	3.6	4.7
	SVM	0.65	2.9	3.8

Note. CP, crude protein; DM, dry matter; IVTD, in vitro true digestibility; NDF, neutral detergent fiber; NDFD, neutral detergent fiber digestibility; nRMSE, normalized root mean square error; PLS, partial least squares; RF, random forest; RMSE, root mean square error; SRI, simple ratio quality indices; SVM, support vector machine. All values are averages of the validation RMSE and R^2 obtained from the 100 models built during the iterative calibration/validation process.

visible range and red-edge regions, with the best combination obtained for the 550 and 710 nm bands, with an R^2 of 0.44.

Estimated values of each quality variable were computed as the average of the iteratively adjusted MR. Each type of model showed different estimation performances for each quality variable (Figure 5, Table 1). For IVTD and NDF, the best results were obtained with PLS regression (validation RMSE of 18.6 and 38.2 g kg DM^{-1}, respectively). For CP and NDFD, the best results were obtained with SVMs (validation RMSE of 21.2 and 2.8 g kg DM^{-1}, respectively).

Overall, PLS and SVM showed similar ranges of estimation performances and systematically outperformed SRI and RF. Figure 6 shows the scatterplots of observed vs. estimated values for each quality variable as computed by the best models; that is, PLS for IVTD and NDF, and SVM for CP and NDFD.

Each variable shows a good fit between laboratory-measured and spectrometry-estimated values. Linear regression lines show a slope and intercept very close to the 1:1 line, which suggests that no bias affects the regression models. The 95% confidence intervals of each model confirmed that there was no statistical significance of slopes being different to 1 or intercepts different to 0. The differences of performances reported in Table 1 are also illustrated in Figure 6, with more scatter for CP than for the other variables. On the other hand, NDF appears to have the least dispersion around the 1:1 line.

Comparison of model performances is summarized in Table 1. Simple ratios and RFs show similar accuracies with low R^2 and relatively high RMSE for all variables. Partial least squares and SVM can also be grouped in terms of performances, with validation R^2 ranging between 0.49 and 0.78. Root mean square error were consistently lower than the ones obtained for SRI and RF.

Four types of models were tested in this study: SRIs, PLS, RF, and SVM. Simple ratio quality indices and, surprisingly, RF, showed poor performances in terms of R^2 and RMSE, whereas PLS and SVM showed relatively good performances. It is interesting to note that, despite the fact that the important regions of the light spectrum for estimating the nutrition quality of forages is located in the short-wave infrared range, that is, between 1,400 and 2,400 nm (Norris et al., 1976), it was possible to estimate CP, IVTD, NDF, and NDFD with reasonable accuracy from a sensor measuring light information between 400 and 1000 nm only, as previously reported by Biewer et al. (2009).

Simple ratio quality indices showed poor estimation performances (Table 1), yet similar to what was reported in Biewer et al. (2009). The bands of importance were mostly located in the visible and red edge spectral regions. Crude protein-adjusted SRI was obtained with information from the blue spectral region. Kawamura et al. (2008) isolated the most important bands from a PLS model to estimate CP and reported that both the blue and red edge regions were of importance. This could be explained by the fact that CP is indirectly linked to the chlorophyll canopy content (Evans, 1989), which can itself be linked to the spectral information contained in the blue region (Curran, 1989). In vitro true digestibility and NDF showed similar patterns in terms of important spectral regions, with an emphasis over the 700–850 nm range (red edge and NIR). It is possible that the relatively good estimation performances obtained in this study are due to the inverse relationship between both IVTD and NDF with the biomass accumulation (Lemaire & Belanger, 2019). Indeed, the red edge and NIR regions are the ones sensitive to the leaf surface increase and, by extent, to the changes in biomass. Most important regions for NDFD are clustered in the green and red edge areas of the light spectrum. Similar to IVTD and NDF, there is an inverse relationship between biomass accumulation and NDFD. This could explain why the red edge region is of importance, as the interest of this region for biomass estimation has been reported in various studies (e.g., Mutanga & Skidmore, 2004)

Random forest showed the poorest estimation performances, with similar or even slightly higher ranges of RMSE compared with SRIs. To the best of our knowledge, this is the first time that such poor performances are reported. Fernández-Habas et al. (2022) noted that PLS outperformed

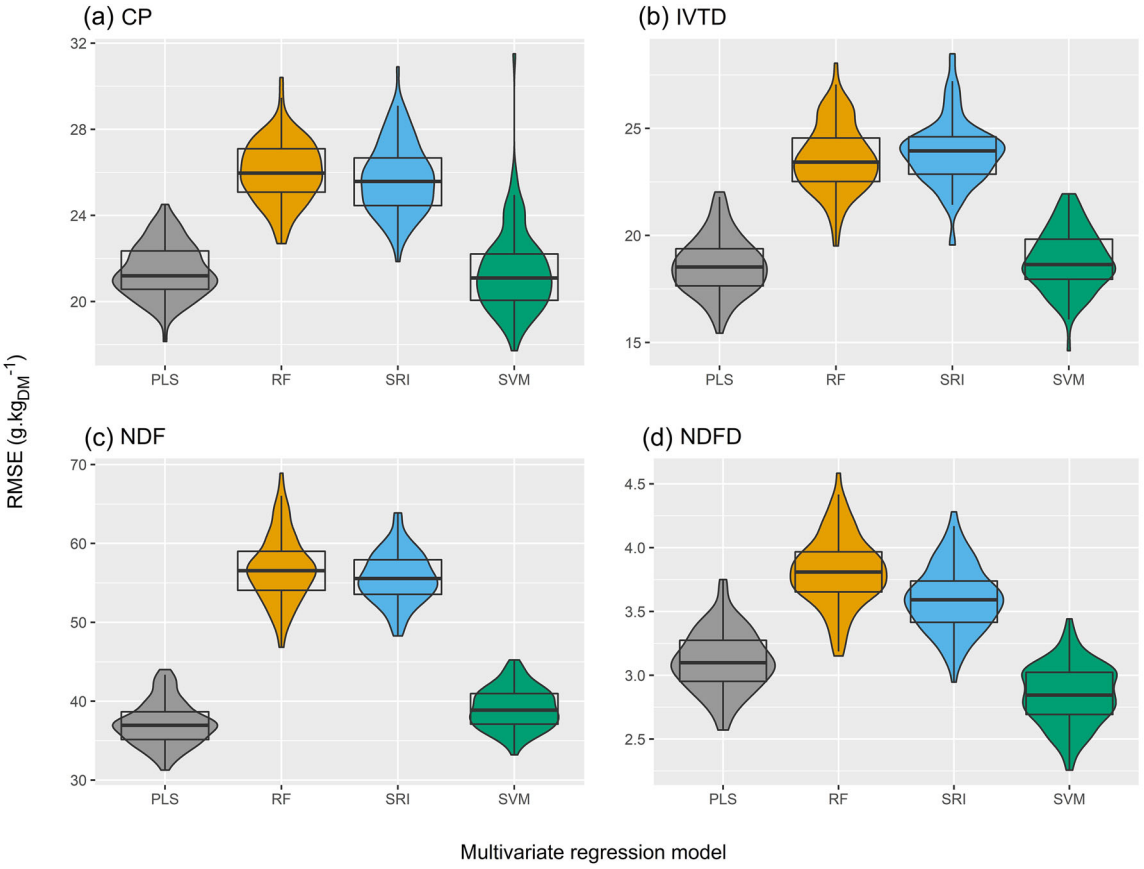

FIGURE 5 Distributions (violin plots) and main quartiles (boxplots) of the iterative validation performances of the simple ratio approach and the three multivariate regression models, for each quality criteria. PLS, RF, SRI, and SVM stand for partial least square, random forest, simple ratio index and support vector machines, respectively

RF for CP and NDF estimations from FieldSpec measurements of Mediterranean grasslands—yet the discrepancy of R^2 values between PLS and RF was smaller than in the present study (e.g., 0.79 and 0.60 for CP estimated by PLS and RF, respectively). Interestingly, RF performances dramatically increased when applying a simple Savitzky-Golay smoothing filter (results not presented here). This could suggest that, in this specific case, the noise included in the spectral data is limiting the performances of RF, yet it has been reported that RF showed good resistance against the effects of noise (Agjee et al., 2018). Nevertheless, in this study, we intentionally used the reflectance data without any preprocessing other than scaling for PLS and SVM. The influence of denoising techniques such as smoothing algorithms and wavelength transformations will be further investigated in an upcoming study with a larger dataset.

Although SVM tended to yield the highest accuracies for calibration, validation results suggest that performances are balanced between PLS and SVM. Sun et al. (2021) used FieldSpec 4 data from a subset of the current dataset and showed that PLS was more robust than SVM for estimating various quality traits. However, opposite results were obtained by Zhou et al. (2019), where the authors showed that SVM systematically outperformed PLS to estimate dry matter yield and CP content of leys from YNS spectral data. Partial least squares and SVM both require fine tuning to limit the risk of overfit, through the selection of an optimal number of latent variables (PLS) or the adjustment of the hyperparameters (SVM). The differences of performances between both methods shown in this study might be due to their respective tuning approaches. More generally, Chlingaryan et al. (2018) reported that the relative performances of MR (e.g., PLS, SVM, RF, and artificial neural networks) for N estimations are largely changing between studies; that is, thus far, there is no algorithm that is expected to systematically stand out for N (and, by extension, CP) estimations. Interestingly, the range of accuracies obtained in both the current study and Sun et al. (2021) are similar, although the spectral range of the YNS is much smaller, and the spectral sampling much coarser, compared with what is obtained from a FieldSpec 4. The authors reported that, of the different spectral regions measured by the FieldSpec 4, the most important ones for CP, IVTD, NDF, and NDFD were all located in the visible range. This could explain why similar accuracies were

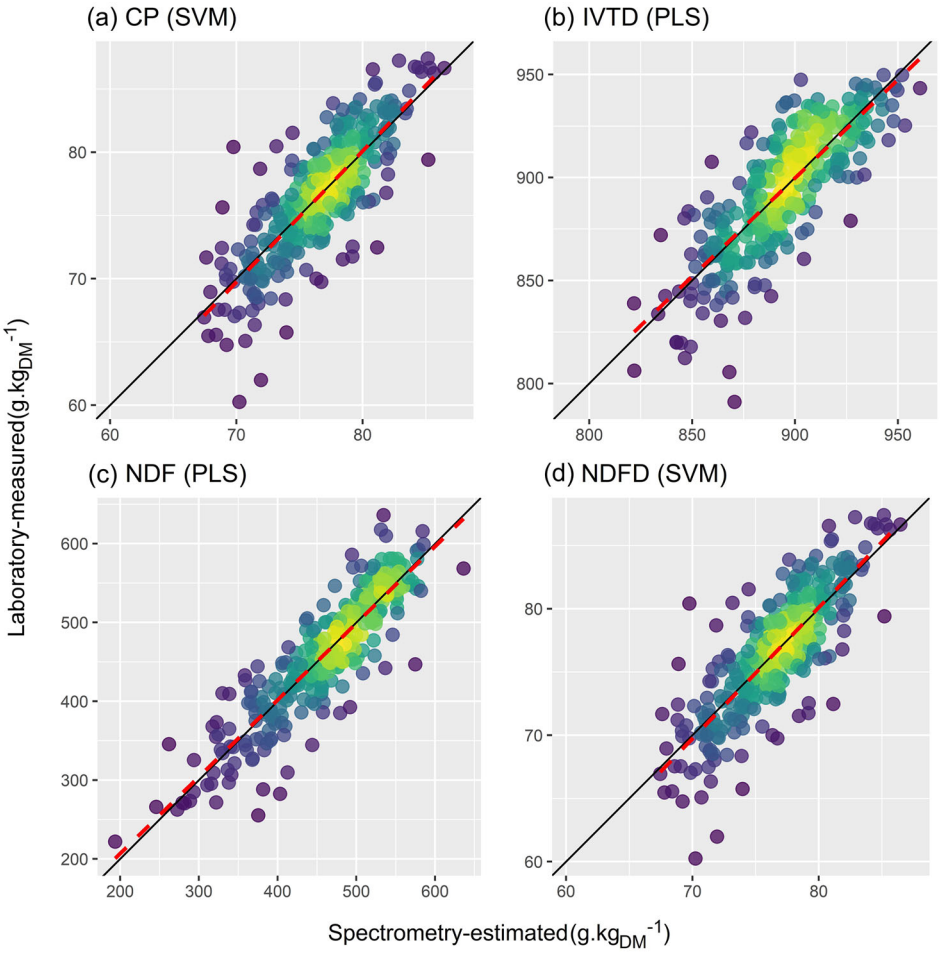

FIGURE 6 Scatter plots of spectrometry-estimated (*x* axis) vs laboratory-measured (*y* axis) values of each quality variable. Estimated values of in vitro true digestibility (IVTD)and neutral detergent fiber (NDF) were determined using partial least squares (PLS) models, and estimated values of crude protein (CP) and neutral detergent fiber digestibility (NDFD) were determined using support vector machine (SVM). All *x* values are averages of the 100 models built during the iterative calibration/validation process. The red dashed lines show the regression line, the black lines show the 1:1 line

obtained despite much poorer spectral information, as the visible range is also measured by the YNS. More generally, the ranges of accuracies (R^2 and RMSE) obtained in this study for CP and NDF are similar to those reported in previous studies. Biewer et al. (2009) reported an R^2 of 0.83 and a standard error of cross validation of 31.2 g kg DM^{-1} (i.e., 15% of error) for CP prediction with a FieldSpec Pro. Duranovich et al. (2020) obtained R^2 of 0.77 and 0.55 for CP and NDF, respectively, from an ASD FieldSpec 4 High-Resolution spectroradiometer. Similarly, Fernández-Habas et al. (2022) used an ASD FieldSpec spectroradiometer and obtained R^2 of 0.70 to 0.79 for CP estimations using PLS and RF, respectively, and R^2 of 0.52 to 0.6 for NDF using PLS and RF, respectively. Smith et al. (2020) also used an ASD FieldSpec Hi-Res 4 to evaluate the several nutrition traits, including CP and NDF. Their results showed R^2 of 0.41 and 0.30 for PLS-estimated CP and NDF, respectively. Kawamura et al. (2008) used an ASD FieldSpec Pro FR and a PLS model to estimate CP and NDF, and obtained R^2 of 0.38 and 0.24, respectively. Pullanagari et al. (2012) used the same device and regression model and obtained R^2 of 0.78 and 0.75 for CP and NDF, respectively.

Results obtained for the current dataset suggest that machine learning algorithms could provide an acceptable accuracy for important quality traits. Although CP showed a validation error of 13%, IVTD, NDF and NDFD could be predicted with less than 8% error. These validation performances are considered as acceptable for practical applications. However, these models, despite being built upon a dataset of reasonable size (n = 336), are only representative of the soil, light, and farming conditions typically encountered in Northern Sweden. This greatly limits the reliability of the models developed in the current study and their transferability toward a practical farming application at a larger scale. One solution would be to increase the training dataset, as the robustness of machine learning algorithms, and more

generally, any statistical-based method, strongly depends on the size and representativeness of the input data. In this case, the training dataset should include more soil types, slopes, fertilization rates, species mixes, botanical compositions, latitudes, and hours of measurement to build a robust solution.

4 | CONCLUSION

With validation nRMSE of 13.0, 2.1, 8.0, and 3.8% for CP, IVTD, NDF, and NDFD, respectively, the results suggest that the industry-ready YNS field spectrometer, which has been designed to estimate N needs for cereals, has good potential for estimating quality traits of forages. However, the dataset used here is only representative of ley conditions of Northern Sweden. As the robustness of statistical models (especially machine learning such as SVM) strongly depends on the representativeness of the calibration dataset, it is necessary to collect a larger and more comprehensive dataset before aiming for any practical application. From an academic perspective, more work is needed to understand why RF failed at estimating the traits with a satisfactory accuracy. The influence of signal preprocessing on the performances of the different models should also be further investigated.

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AUTHOR CONTRIBUTIONS

Julien Morel: Data curation; Formal analysis; Methodology; Writing – original draft; Writing – review & editing. Zhenjiang Zhou: Conceptualization; Data curation; Funding acquisition; Project administration; Writing – review & editing. Leonardo Monteiro: Formal analysis; Writing – review & editing. David Parsons: Data curation; Formal analysis; Funding acquisition; Methodology; Supervision; Writing – review & editing.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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