Estimation of Ley Quality with the Arable Mark 3

- A Commercial Field Spectrometer

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Estimating ley quality with the Arable Mark 3: a commercial field spectrometer

Estimering av vallkvalitet med Arable Mark 3: En kommersiell fältspektrometer.

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Abstract

Ley is the most widespread crop in Sweden and is the base of ruminant diets. Improving ley quality is necessary for increasing the proportion of forage in ruminant diets, offering both environmental and economic benefits. Harvest timing is critical to achieving the desired ley quality, but a decision support system for optimizing all harvests is currently lacking. Remote sensing is a promising tool, and the Arable Mark 3 (AM3), a low-cost commercial field weather station including a spectrometer with 21 bands, has the potential to estimate ley quality directly in-field. The purpose of this study was to evaluate the potential of AM3 as a decision support tool to assist farmers in determining the optimal time for harvesting ley. The AM3 was evaluated using two devices: one stationary, which collected weather and plant data throughout the season, and one mobile unit, which served as the primary data collector for analysis. The stationary AM3 demonstrated the versatility of the AM3 as weather station. The mobile AM3 measured spectral reflectance from the ley, followed by cutting the ley for laboratory analysis of nutritive values. A total of 43 ley samples were analysed across two regions in Sweden during the 2024 growing season. Multivariable regression models, including multiple linear regression (MLR), partial least squares (PLS and caretPLS), and support vector machine (SVM), were applied to find relationships between spectral data and laboratory analyses of crude protein (CP), metabolizable energy (ME), neutral detergent fibre (NDF), organic matter digestibility (OMD), and dry matter (DM). PLS, caretPLS and SVM used internal tenfold cross-validation to prevent overfitting. MLR lacked regulations, likely resulting in overfitting. Using data from narrow bands alone gave the lowest R^2 (0.59-0.71), while combining narrow and wide bands increased R^2 (0.59-0.87), mainly for CP and NDF. The results showed that PLS performed best for CP and NDF. caretPLS and SVM performed for ME, OMD, and DM, with narrow bands alone and narrow and wide bands together. Adding additional spectral data from the AM3 such as normalized difference vegetation index and chlorophyll index as auxiliary predictors improved R^2 (0.75-0.82) for ME, OMD and DM, with risk of overfitting. The study highlights the potential of the AM3 as a practical decision support tool for timing all ley harvests but much larger diverse datasets are necessary to build reliable predictive models. Involving farmers in decision support system development will ensure applicability of the AM3.

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Abbreviations

AM3	Arable Mark 3
ASD FS	ASD Fieldspec
BFE	Backward feature elimination
CI	Chlorophyll index
CP	Crude protein
DM	Dry matter
IVTD	In vitro true digestibility
ME	Metabolizable energy
MLR	Multivariable linear regression
NDF	Neutral detergent fibre
NDFD	Neutral detergent fibre digestibility
NDVI	Normalised difference vegetation index
NIR	Near infrared
OMD	Organic matter digestibility
nm	Nanometer
PLS	Partial least squares
RMSE	Root mean square error
RPD	Residual predictive deviation
RRMSE	Relative root mean square error
R^2	The coefficient of determination
SWIR	Short-wave infrared
SVM	Support vector machine
VOS	Rumen liquid dissolvable organic substance
WSC	Water soluble carbohydrates
YNS	Yara N-sensor

1. Introduction

1.1 Ley production in Sweden

Benefits with ley production

Ley, together with other green forage crops, forms the largest crop group in Sweden, covering 38% of agricultural land (Olsson 2024). Ley refers to temporary forage crops that are in rotation with other crops and often consist of perennial grasses and/or legumes and sometimes herbs, primarily used as feed for ruminants and horses.

Cultivation of ley contributes to mitigating greenhouse gas emission through carbon sequestration by promoting stabilization mechanisms of soil organic matter (Rasse et al. 2005; Cotrufo et al. 2013; Kätterer et al. 2017; McGowan et al. 2019; Chen et al. 2022). Since the 1980s, the increase in ley cultivation in Sweden has raised soil organic matter in mineral soils by an average of 7.7% from 1988 to 2017 (Poeplau et al. 2015; Kätterer et al. 2017).

Cultivation of ley enhances yield of subsequent crops by improving soil structure which leads to better nutrient availability and water retention (Lal 2004; Tidåker et al 2016). It reduces nutrient leaching, fosters biodiversity, and, when legumes are included, contributes nitrogen (N) to the soil (Lindén 2008; Bergkvist & Båth 2015; Tidåker et al. 2016; Ahlgren et al. 2022). Ley also suppresses weeds through competitive growth and regular harvests and breaks pest and disease cycles (Andersson & Milberg 1996; Sjursen 2001, cited in Nilsson et al. 2022 p.7; Kirkegaard et al. 2008). The positive effects on subsequent crop yields can persist for up to three years after ley cultivation (Bergkvist & Båth 2015).

Ley as feed for ruminants

The climate in Sweden provides good conditions for ley to grow, which can be cultivated on all type of agricultural soils in Sweden, and hence is the base of Swedish ruminant diets. The main ley quality aspects are metabolizable energy (ME), crude protein (CP) and neutral detergent fibre (NDF). By raising ME and CP, and limiting the NDF, a higher ley quality and increased feed intake enables a greater proportion of forage in ruminant diets (Gunnarsson et al. 2014). This provides a sustainable alternative to feed supplements for Swedish meat and dairy farmers, offering both economic and environmental benefits (Finn et al. 2013).

When striving for high yields, balancing yield and the nutritive value is easier said than done. When plants grow, structural fibres are needed for support, which increases NDF, but lowers the CP concentration and ME content (Gustavsson 1995). Hence, early harvest results in higher ley quality but also in reduced yields because the plants are still in an earlier developmental stage at the time of cutting (Gunnarsson et al. 2014). Several and early harvests mean that a larger portion of the growing season is occupied by plants with lower growth potential. Choosing the optimal harvest date is key to formulating the most cost-effective feed and reduce the need for concentrates (Gustavsson 1995).

Improved ley production and feed efficiency

In a report by Lantmännen (2021), one of Northern Europe's leading agricultural market players, it is highlighted that improved ley production is important to reduce the climate impact of Swedish meat and dairy production. A key factor is ensuring that animals receive the right feed to maintain health and productivity. By setting targets and monitoring ley quality, farmers can improve feed efficiency and produce as much feed as possible on the farm. High feed efficiency is economically beneficial and reduces greenhouse gas emissions per kilogram of meat or milk. Analysing ley quality helps optimize the feed for different animal groups, simplifying planning for feed distribution in terms of quality and quantity.

Lantmännen (2021) address that to help farmers optimize ley quality to use it efficiently, technical solutions that provide data for decision-making are needed, ideally directly on the farm. Financial support may be needed to encourage investments in new technology for improved farm management. Another problem that must be resolved, is the question of data access from different systems. Reviews by Villa-Henriksen (2020) and Schellberg et al. (2008) also identified the cost of implementation of new technical solutions as a challenge as well as collaboration across the agricultural industry regarding the data sharing. Nettle et al. (2022) also underscore that new technical solutions should be focused on the farmer, which includes fast and easy adoption and increased profitability and skill.

In summary, there is a need to improve ley production and feed efficiency, with the timing of ley harvest being a critical factor for balancing yield, protein, and energy. Harvesting late increases yield but dilutes CP and reduces ME due to higher NDF. Thus, there is a demand for a tool that acts as a decision support system to determine the optimal timing for ley harvest. This system would enable farmers to maximize the nutritional quality and economic value of ley and offer environmental benefits by improving soil health. To face the challenges, the cost must be limited and data useful and accessible. For widespread adoption, the tool should combine simplicity with relatively good precision and pay-off.

1.2 Decision support systems in ley cultivation

Vallprognos

Vallprognos is a web-based tool (http://www.vallprognos.se/) using degree days to provide a forecast for the first harvest. The tool provides a diagram with a “normal curve” which represents the average development of ley from the years of 1991-2020 and a “forecast curve” which represents the development for the current season. By comparing the forecast curve with the normal curve, one can see if the first harvest will be early or late (Vallprognos 2023). A total number of degree days of 250 is considered to provide an energy value for timothy of 11 MJ/kg, which is a suitable lower limit for milk cows. The recommendation is that the ley should be harvested before then. The forecast is built on measured and forecasted degree days provided from SMHI’s measurement stations around Sweden. Every year, sample harvests are taken and analysed for ME, CP, and NDF, provided as an extra support basis for the farmers.

In a Master’s thesis, Ragnmark (2012) assessed the accuracy of forecasting energy values based on degree days. The results highlighted the need for adjustments of the degree-day, as significant variations in the optimal harvest time were observed across different regions in Sweden.

Plant development, and consequently the nutritive value of the ley, is mainly dependent on temperature (Gustavsson 1995), and is why degree days and Vallprognos are useful as prediction tools. However, factors like light, water, nutrient availability, species composition, and management practices influence plant growth and development, thereby affecting the nutritive value of the ley (Biewer et al. 2009; Gustavsson 1995). In addition, Vallprognos is limited to the first harvest. Rinne et al. (2002) explored the possibility of using degree days to estimate regrowth and concluded that additional parameters are necessary for accurate predictions. Hence, there is demand for a tool that provides real-time, site-specific estimations with minimal dependencies, and with applicability to all harvests for more precise predictions of ley nutritive values. Remote sensing presents a promising alternative to provide this.

Satellites

Satellites can be used to assess ley biomass, N content and N uptake, often based on vegetation indices such as normalized difference vegetation index (NDVI). Satellites are effective for covering large areas and benefit from open-access satellite data (Peng et al. 2023a). Currently, satellites are not used for assessing ley quality in Sweden. However, an ongoing VallSAT project, in collaboration with DataVäxt, a Swedish agricultural technology and software company, aims to explore if satellite imagery can be used to do this (Peng et al. 2023b). The project seeks to develop a decision support system that integrates satellite data with simple crop models. It is designed to be like the widely used web-based tool “CropSat”, developed by Söderström et al. (2015) (https://cropsat.com/se/), which allows users to visualize biomass variations within fields and generate N distribution maps. However, final results from the VallSAT project have not yet been published. Morel (2022) published some early preliminary results which showed potential in estimating CP and NDF.

Limitations with satellites may include the relatively low spatial resolution of the openly available sources (e.g., 10 m for Sentinel-2) in comparison to sensors on board of other platforms and the presence of clouds that can hinder capture of useful images from optical sensors. While older satellite images can still provide insights into biomass estimation and N distribution, more time-sensitive tasks, such as determining the optimal harvest timing, may be challenging. Their temporal resolution may differ depending on the latitude (e.g., ~2-5 days for Sentinel-2) and the time to acquire, process and use the images for agricultural assessments make real-time decision-making difficult.

Drones

Oliveira et al. (2023) evaluated the performance of drones in estimating quality parameters of grass swards, including N concentration, OMD, NDF, and water-soluble carbohydrates (WSC). The study used hyperspectral cameras with spectral ranges in the visible near infrared (VNIR, 400–1000 nm; 224 bands) and short-wave infrared (SWIR, 900–1700 nm; 224 bands). However, the models created were unable to explain much of the variation in ley quality. Additionally, using drones for such analyses is time-consuming and technically challenging. While drones have potential, they are not yet suitable for practical application.

ASD FieldSpec

Field spectrometers currently offer a more developed and viable tool for ley quality estimations. A drawback with this technology is that it measures only one field spot, instead of the whole field as satellites and drones offer.

The ASD FieldSpec (350-2500 nm range) is a field spectrometer and has been tested numerous times with satisfactory results in estimating the ley quality parameters such as ME, CP, NDF, in vitro true digestibility (IVTD), NDF digestibility (NDFD) ash, and dry matter (DM) yield, (Biewer et al. 2009; Duranovich et al. 2020; Fernández-Habas et al. 2022; Sun et al. 2022). While the ASD FieldSpec provides highly detailed plant information due to its numerous narrow spectral bands, it is a research-grade instrument. It has a high cost and is complicated to calibrate, use, and process the data, making it unsuitable for practical use by farmers.

Yara N-sensor

In contrast, commercial field spectrometers offer a restricted spectral range with fewer bands and coarser resolution (Morel et al. 2022). These features make them more affordable and user-friendly making them a practical choice for farmers and agricultural advisors. The Yara N-sensor is a commercialized spectrometer (400-1000 nm range) and is made to optimize N fertilization in cereals. Both Zhou et al (2019) and Morel et al. (2022) evaluated the Yara N-sensor for estimating ley quality parameters, including N-uptake, CP, NDF, IVTD, NDFD, and DM yield. Both studies achieved satisfactory results. However, the studies were geographically limited to Northern Sweden and to one season. Larger datasets including more locations and years, testing how well these models work in real farm situations are needed.

Sensors can be categorized as passive or active. An active sensor has its own light source, so it can be used in low light conditions, while the passive cannot (Fitzgerald 2010). The spectral information from the active sensor is typically limited due to fewer spectral bands, while the passive provides more spectral information. The Yara N-Sensor has undergone modifications going from a passive to an active sensor to facilitate a tractor mounted sensor that can be used in a wider range of light conditions, including darkness. This version of the Yara N-Sensor has fewer spectral bands, selected primarily for focusing on N content in cereals. Although there are no published results of testing the active light source Yara N-Sensor in leys, it is likely to reduce its overall accuracy for ley quality assessments.

Arable Mark 3

There are already sensors that function as automated weather stations to provide farmers with infield weather data to monitor crop health and optimize cultivation. Arable is one company that provides this type of sensor (Arable.com). Arable (2021) conducted a study of their own to investigate the benefits of infield weather data. Included discrepancies revealed overestimated rainfall by as much as 361% and growth stages as much as 9 days premature. Besides the weather station, a spectrometer primarily for measuring NDVI has been added, resulting in Arable Mark 2 (AM2), an automated and low-cost radiometer.

Pathiranage et al. (2023) reviewed the potential of the AM2 to collect surface reflectance data and to be used to validate and complement the information obtained from satellite imagery. The AM2 was compared to the high-end ASD FieldSpec. The AM2 provided accurate surface reflectance measurements, with an average deviation of less than 0.1 reflectance units in the blue, green, yellow, and red bands compared to the ASD FieldSpec.

The successor to the AM2, the Arable Mark 3 (AM3), features upgrades, including an expansion from six spectral bands to a 21-band spectrometer (400-1700 nm range) (Arable.com). While the AM3 has yet to establish its full potential, it offers greater spectral resolution than the active Yara N-Sensor. It is available at a comparatively low cost (1499 USD, with additional hub adapter 199 USD, 110 USD for ground anchor and telescoping pole for stationary purposes, and a yearly fee of 649 USD/year for managing data). Additionally, the AM3 is equipped with features for collecting both weather and plant data, making it a versatile tool for farmers. This makes the AM3 a promising alternative for addressing the current limitations of decision support systems for timing harvests to achieve desired ley quality.

1.3 Regression models

Field spectrometers capture variations in spectral reflectance from ley across the visible, NIR and SWIR regions (Sun et al. 2022). Reference data is required to link specific reflectance values to plant attributes. The spectral data is then incorporated into regression-based mathematical predictive models and validated against actual laboratory-analysed values of the ley. This process helps determine whether reliable relationships exist between reflectance patterns and the variables of interest.

The task of regression involves predicting a response variable (Y) based on predictor variables (X) (Wold et al. 2001). To develop regression models linking spectral data (X) with laboratory-measured ley quality parameters (Y), commonly used methods include multiple linear regression (MLR), partial least squares regression (PLS), and support vector machine (SVM).

While MLR works well when X-variables are few and not strongly correlated, spectrometers produce many X-variables and often with high correlation. MLR is a linear model which make it less prone to overfitting but also lacks mechanisms to prevent overfitting. This makes methods like PLS and SVM more suitable to develop regression models for spectrometers. (Coen et al. 2007).

PLS simplifies and creates a linear relationship between X and Y by creating new variables, called PLS components, which maximize the shared variance between predictors and responses (Wold et al. 2001). Since spectrometers produce many predictors, and these data points often overlap, a linear relationship can be difficult to apply (Mountrakis et al. 2011). SVM can also handle nonlinear relationships by mapping variables into a higher-dimensional space using a kernel trick, which makes separating overlapping data points easier. Once in this space, SVM can apply a linear regression.

Overfitting occurs when a model learns to fit the training data too closely, including its noise or irregularities, instead of capturing the general patterns or rules that apply to unseen data. This leads to high accuracy on the training dataset but poor performance on new or unseen datasets, as the model fails to generalize (Dietterich 1995).

PLS is primarily designed for linear modeling, which inherently reduces the risk of overfitting compared to nonlinear methods like SVM. However, for datasets with nonlinear relationships, this simplicity can limit the predictive performance of PLS. Overfitting is minimized in PLS by focusing on the most significant components of the data by selecting an appropriate number of latent variables. Using too many latent variables can lead to overfitting, as the model may capture noise instead of meaningful patterns. PLS applies manual cross-validation to find the most suitable model (Coen et al. 2007). caretPLS is a version of PLS in the caret package in R, where the cross-validation process is automated and optimized.

SVM incorporates a regularization parameter (C) that controls the trade-off between fitting the training data well and keeping the model simple. A larger C allows the model to fit the training data more closely, which can lead to overfitting. Smaller C values prevent overfitting by simplifying the model. SVM uses cross-validation to determine the optimal values for C, ensuring that the selected model generalizes well to unseen data (Coen et al. 2007).

1.4 Objectives

The aim of this study was to evaluate the potential of the AM3 to estimate ley quality in the field, and to be used as a decision support tool to help farmers in their decision making in timing of ley harvests. At the moment, there is no available commercial decision support system based on remote sensing of ley quality in Sweden, and this is something that the master project will contribute to develop. The study also examined the comparative performance of regression models. The objectives of the study were:

1. Evaluate how well the stationary AM3 measures plant and weather data.
2. Develop regression models for in-field ley quality, using spectral data obtained through using mobile AM3 devices.

2. Materials and methods

2.1 Data collection

The AM3 sensor was deployed in two ways: i) a stationary AM3 was placed in a ley field to continuously collect location-specific qualitative plant and weather data throughout the growing season (Figure 1), which is what the AM3 is originally made for; and ii) a mobile sensor was used to collect quantitative spectral data, followed by cut ley samples for laboratory analysis. The reflectance data were then correlated with laboratory measurements using the regression models to assess the AM3's predictive performance.

The stationary AM3 was installed in a four-year-old field dominated by timothy and white clover. It was removed and reinstalled during harvest and fertilization.

With the mobile AM3, a total of 43 ley samples were collected over the 2024 growing season from two regions: 16 samples from Västmanland and 27 from Västerbotten (Röbäcksdalen).

The samples from Röbäcksdalen came from two different fields, both two-year-old leys, with a species composition dominated by timothy and red clover. The botanical composition of the samples varied from 0-69% clover and spanned all three harvests conducted in the fields.

The samples from Västmanland were more diverse, coming from nine different fields with ages ranging from one to four years old. Some fields consisted of pure grass swards with either perennial ryegrass, timothy, or cocksfoot, while others were mixed swards with timothy and red and/or white clover (20-50%) or lucerne (10-85%) combined with cocksfoot and/or perennial ryegrass. Data collection in Västmanland primarily focused on the second and third harvests. However, some fields were extensively cropped, making it unclear whether the samples were close to the second or third harvest.

Figure 1. The stationary sensor.

Sampling equipment included two AM3 (one stationary and one mobile), a telescoping pole with ground anchor, a light stand, scissors, a 50 x 50 x 8 cm quadrat, recording sheets, sample bags, labels, a ruler, and phenology keys. Sampling times were flexible, spaced throughout the season and clustered around harvests. Due to setup complexity, a limited number of samples was collected.

The spectral data was provided in 5-minute intervals. The AM3 required a setup period of 5-15 minutes to stabilize before and after collecting data. Unstable spectral data were removed before data analysis. This included 1-2 intervals (5-10 minutes) in the beginning and depending on if the sensor had time to shut down or not, also one interval (5 minutes) at the end.

During field sampling, the procedure began within two hours of solar noon, under stable weather conditions (either clear or consistently overcast skies). A representative area in the field was selected and high-weed zones were avoided. The light stand was adjusted to position the spectrometer one meter above the plant canopy, with the solar panel oriented away from the sun to avoid shadows falling upon the ley that was measured. Upon activating the mobile AM3, field observations were recorded, including dominant grass and legume species, estimated botanical composition (grass, legume, weed), phenological stages of the main species, canopy height, harvest number, and GPS location. The AM3 was then left to collect data for 30 minutes (Figure 2), extended to one hour during initial trials. The mean value of stable spectral reflectance measurements of each sample was used for data analysis.

Figure 2. Mobile AM3 spectral measurements.

After spectral data collection, the AM3 was turned off, the quadrat was placed directly under the spectrometer (Figure 3), and the sensor was moved away. A photo was taken directly above the quadrat area (Figure 4). The ley within the quadrat was cut to an 8-cm stubble height and stored in a labelled sample bag with project information, date, and a unique ID. The samples were weighed directly after cutting to record the wet weight (Figure 5). Samples were transported to the lab immediately.

In the laboratory, each sample was dried at 60°C for 48 hours or until reaching a stable weight. The final dry weight was recorded, and samples were stored for further quality analysis.

N fertilizer rates were excluded from consideration because the N contribution from manure is challenging to quantify, and is not directly comparable to mineral N.

Figure 3. Quadrat placed where spectral data was measured.

Figure 4. Photos taken directly over the quadrat.

Figure 5. Ley within the quadrat cut to an eight-cm stubble height and stored in a labelled sample bag (to the left) and samples weighed directly after cutting (to the right).

2.2 The Arable Mark 3

Arable is an agricultural data analytics company that combines hardware, software, and data science, made for the farmer to support optimal cultivation management. The AM3, is an all-in-one weather station and crop monitor that collects over 40 weather and plant measurements. It can withstand harsh conditions and is solar powered, and it features sensors for rainfall, light, temperature, and plant health. Arable uses a global calibration and validation network across 35 research sites in 11 climate zones. This network ensures that the AM3 measurements are calibrated against research instruments, such as radiometers for solar radiation. The collected data is used to train machine learning models, allowing the device to refine its predictions over time without hardware updates. The AM3 has on-board satellite links which gives the user data in real time (Arable 2020). The AM3 data can be accessed from its application program interface.

The AM3 spectrometer measures upwelling and downwelling irradiance across 21 different wavebands ranging from 400 nm to 1700 nm (Arable 2022) (Figure 6). Fourteen wavebands are narrow bands, covering the visible spectrum and the beginning of near infra-red (NIR) region. Seven wavebands are wide bands, covering whole NIR and short-wave infra-red (SWIR) region. By using the upwelling and downwelling irradiance, the plant surface reflectance (the proportion of incoming solar radiation reflected by the plant surface) was calculated using Equation 1.

Equation 1. Spectral reflectance calculation. R is the reflectance, and I is the irradiation.

$$R = \frac{I_{upwelling}}{I_{downwelling}}$$

As already mentioned, does the AM3 measure both weather and plant variables. In this project, a small selection of these was analysed, including precipitation (mm), temperature (°C), wind speed (m/s), normalized difference vegetation index (NDVI), and chlorophyll index (CI). NDVI assesses overall vegetation vigor and is linked to the canopy leaf area index (LAI) (Arable 2022). It is calculated using reflectance in the red bands and near infra-red (NIR) spectra, based on methods from Tucker (1979). The CI is associated with N uptake during peak greenness. Its calculation, based on Gitelson et al. (2005), compares specific spectral ranges with chlorophyll content.

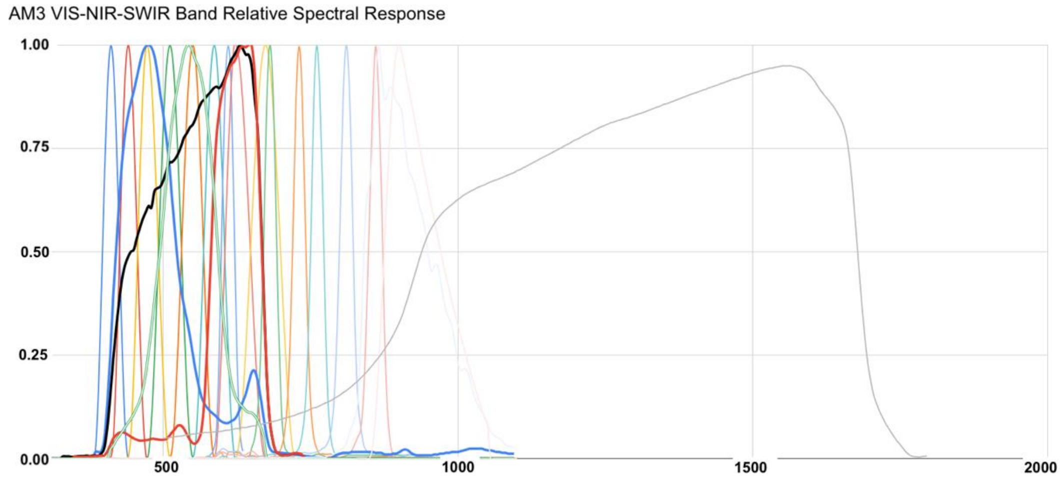


Figure 6. Arable Mark 3 (AM3) wavebands and corresponding spectral regions in the visible (VIS) near infra-red (NIR) and short-wave infra-red (SWIR) spectrum. The fourteen wavebands with consistent patterns and distinct peaks are classified as narrow bands, while the seven wavebands with irregular patterns are categorized as wide bands. Figure provided by Debonte (2024 personal communication[1]).

2.3 Lab analysis

Ley samples were analysed at Agrilab Uppsala for CP, ME, NDF, organic matter digestibility (OMD), and dry matter (DM). These ley quality parameters were determined using NIR spectroscopy (NIRS) with the NIRS DS 2500 F (FOSS 2018). The DS 2500 F is a NIR monochromator (850 to 2500 nm range) with a spectral resolution of 0.5 nm. The lab analysis followed the standard method used in forage feed analyses.

For CP and NDF, the NIRS models were trained to analyse ley samples. These models were initially developed and using wet chemistry methods (Ulfik 2025, personal communication[2]). The samples were dried and ground to pass through a 1 mm sieve. CP was determined using the Dumas method, where N content was measured with an N-analyzer and multiplied by 6.25 (AOAC 1990). NDF was determined using the Van Soest et al. (1991) method, which involved treating samples with sodium-dodecyl-sulfate to remove non-fiber components, followed by drying and weighing the residue.

DM was measured by drying ley samples at 60°C, followed by reweighing to calculate moisture loss. The residual water content was then analysed using DS 2500 F. (Ulfik 2025, personal communication).

ME and OMD were calculated based on rumen fluid-soluble organic substance (VOS), determined through a five-day incubation process. This process involved

[1] Cedric Debonte, commercial director at Arable, mail communication 2024-12-05

[2] Martin Ulfik, lab technician at Agrilab, telephone call 2025-01-13

treating ley samples with rumen fluid from cows on a specific diet, measuring the outcome with mass spectrometry with the DS 2500 F. The equations for ME and OMD calculations are found in Equation 2Equation 3,Equation 4, andEquation 5. For further details on coefficients and calculations, readers are referred to Spörndly (2003).

Equation 2. Calculation of ME coefficient for ley with less than 50% legumes (Lindberg 1983). Where y is ME per kg organic substance and x is VOS value.

$$y = 0.160x - 1.91$$

Equation 3. Calculation of ME coefficient for ley with more than 50% legumes (Lindberg 1983). Where y is ME per kg organic substance and x is VOS value.

$$y = 0.106x + 2.93$$

Equation 4. Calculation of OMD coefficient for ley with less then 50% legumes (Lindberg 1983). Where y is organic substance digestibility coefficient in percent and x is VOS value.

$$y = 0.90x - 2.0$$

Equation 5. Calculation of OMD coefficient for ley with more than 50% legumes (Lindberg 1983). Where y is organic substance digestibility coefficient in percent and x is VOS value.

$$y = 0.62x + 23.0$$

2.4 Regression models

The programming language R, developed by R core team (2021), was used for data analysis and creating visualizations to present the results. To develop regression models linking spectral data with laboratory-measured ley quality parameters, the methods used were MLR, PLS, caretPLS, and SVM. Regression models were produced using both narrow bands alone, wide bands and narrow bands together, and narrow and wide bands together with addition of auxiliary predictors NDVI and CI. The relative importance of predictors was produced after creating the regression models by using the VarImp function in R. Regression model results were presented in tables and in scatter plots.

Reproducibility was ensured by setting a seed (set.seed(42)) to maintain consistent data partitioning across runs, making results comparable. Root mean square error (RMSE), relative RMSE (RRMSE), and coefficient of determination (R^2) were used to evaluate model performance. The pls and caret package, available in R was used for PLS and SVM regressions (R core team 2021). Since datasets were too small to break up into training and validation datasets, the cross-validation was only an internal validation for model development. MLR did not have any cross-validation.

For PLS cross-validation, the data were split into 10 parts (10-fold repeated cross-validation). The model was trained on 9 parts and tested on the part left out.

This process was repeated 10 times, using a different part for testing each time, preventing the model from overfitting to a specific training set. The optimal number of components was chosen based on the smallest prediction error, ensuring that only the needed number of components were used and avoiding overfitting by not keeping too many components that might just capture random noise.

For caretPLS, a grid search was performed to test different numbers of components (ncomp = seq(1,10, by=1)) using 10-fold repeated cross-validation, preventing the model from overfitting noise. The model with the lowest RMSE on validation data was selected.

A grid search in SVM tested a range of C values (expand.grid(C = seq(0.1,2, length=10)) and used a 10-fold repeated cross-validation to evaluate the model's performance for each value and prevent overfitting. The model selected the C value that gave the lowest RMSE on the validation data.

3. Results

3.1 Lab analysis results

To explore potential differences between the sites, the lab data was divided by location. The lab results are presented as violin and box plots in Figure 7. The median for CP and NDF were lower in samples from Västmanland compared to Röbäcksdalen (166 vs. 181 and 401 vs. 422 g/kg DM, respectively). The same trend applied for ME and OMD, with lower median in Västmanland (10.6 vs. 11.2 MJ/kg DM and 73.7% vs. 77.7%, respectively). DM was an exception, where the median was higher in Västmanland than in Röbäcksdalen (24.1% vs. 20.2%). Overall, samples from Västmanland exhibited a wider distribution of values.

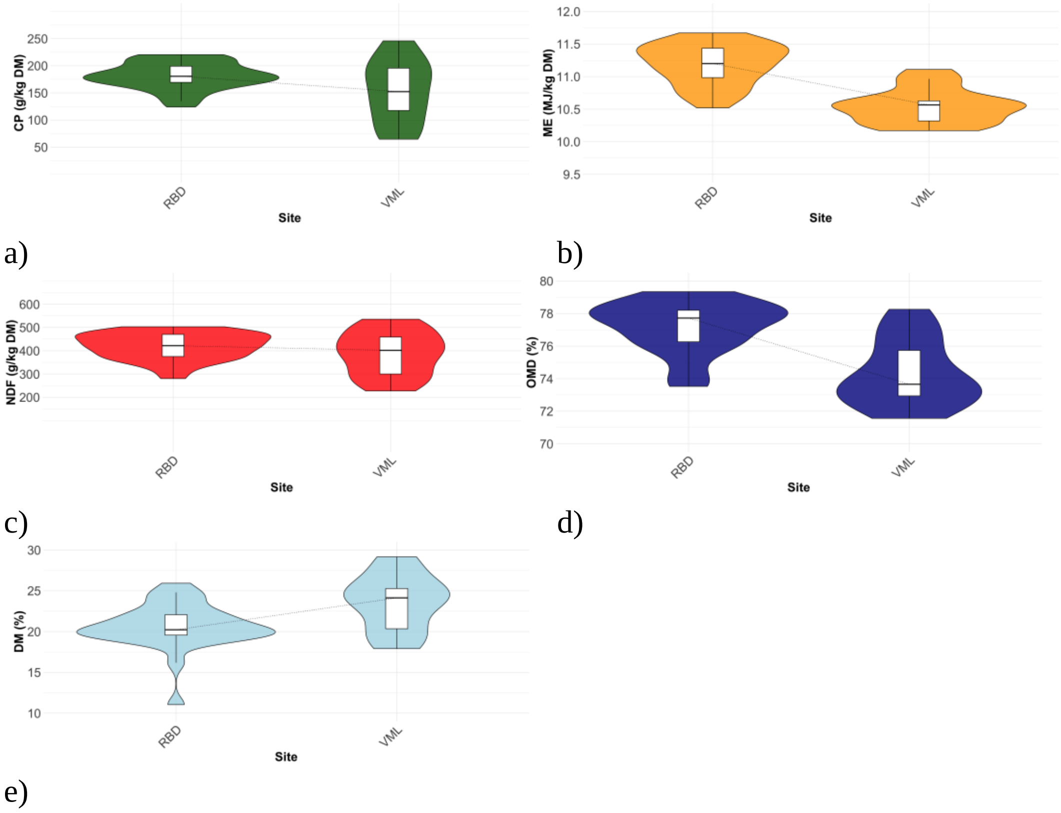


Figure 7. Violin and boxplot visualization of a) crude protein (CP), b) metabolizable energy (ME), c) neutral detergent fibre (NDF), d) organic matter digestibility (OMD), and e) dry matter (DM) divided by site on the x-axis with Röbäcksdalen (RBD) to the left and Västmanland (VML) to the right. The y-axis represents the respective measurements units for each variable. The violin plots represent the distribution and density of observed values, while the boxplots represent the middle 50% of the data (interquartile range, IQR, 25th -75th percentile), with the horizontal line inside indicating the median, The whiskers extend to 1.5x IQR, excluding extreme outliers. Median values across sites are connected by a dotted line for comparison. Violin plots are trimmed to the observed data range.

3.2 Stationary AM3 plant and weather data

The stationary AM3 sensor recorded weather and plant data from May to October, with a temporary break before the first harvest (June 25th) from June 5th to July 5th. The mean temperature had a decreasing trend from August and forward. Precipitation was sporadic across the season. Wind speed fluctuated throughout the season, but the magnitude of variation remained relatively stable (Figure 8).

Daily NDVI and CI had a steep decrease and increase after the first harvest, reflecting big changes in plant biomass. A similar trend, though less pronounced, was observed after the second harvest on July 26th. After mid-August, NDVI and CI showed a consistent declining trend (Figure 9).

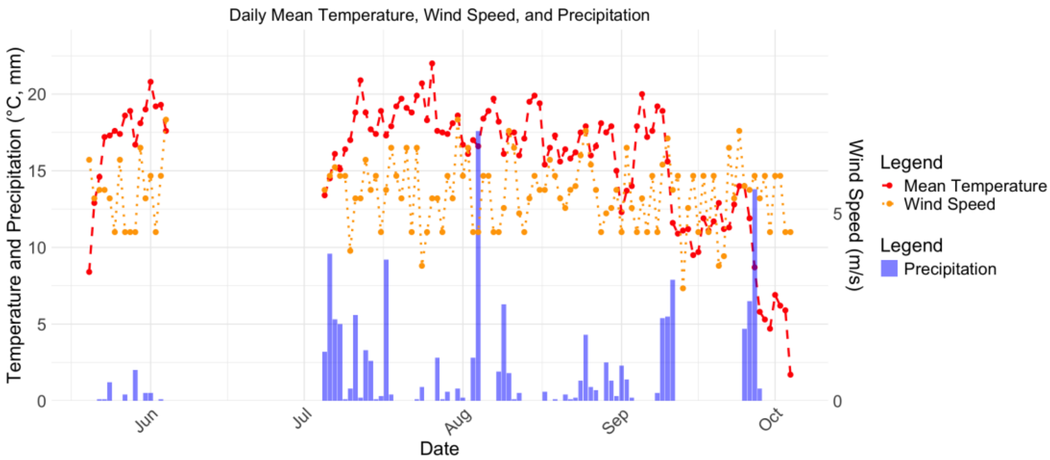


Figure 8. Daily measurements of mean temperature (°C), precipitation (mm), and wind speed (m/s) across the season from the stationary AM3.

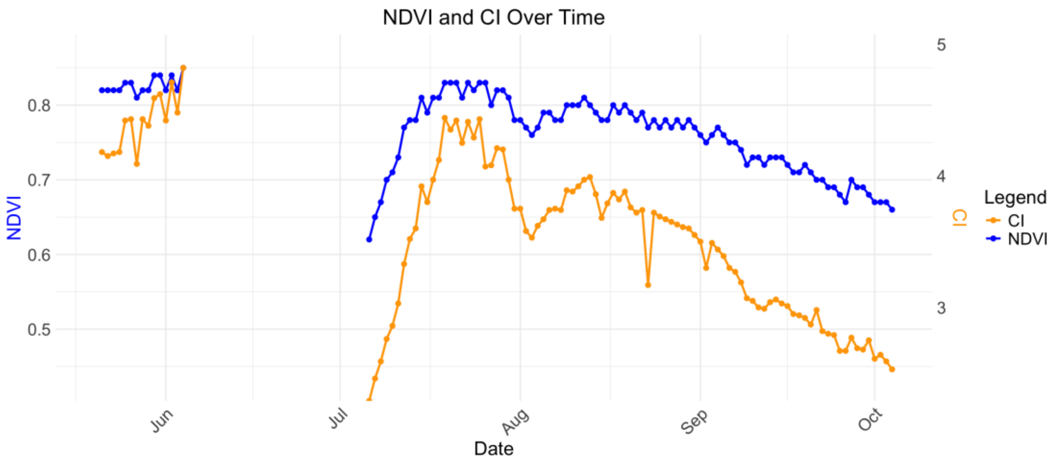


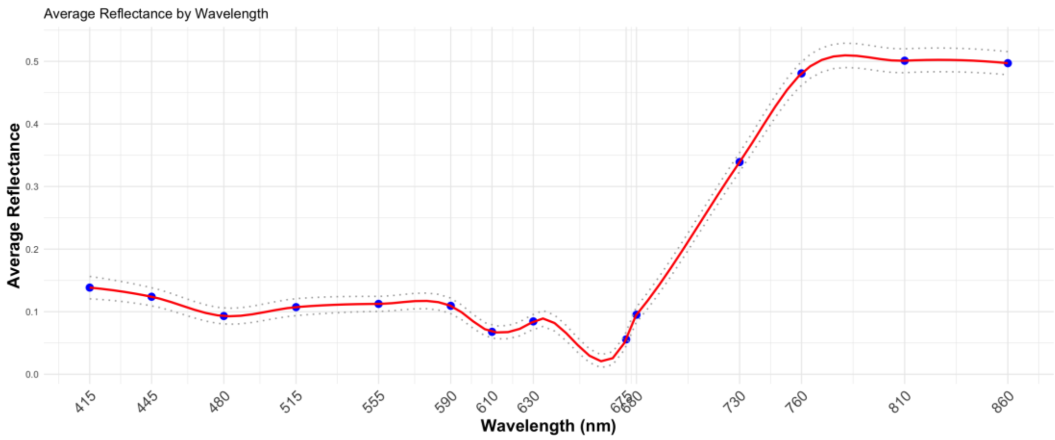
Figure 9. Variation of normalized difference vegetation index (NDVI) and chlorophyll index (CI) across the season from the stationary AM3.

3.3 Mobile AM3 spectral data

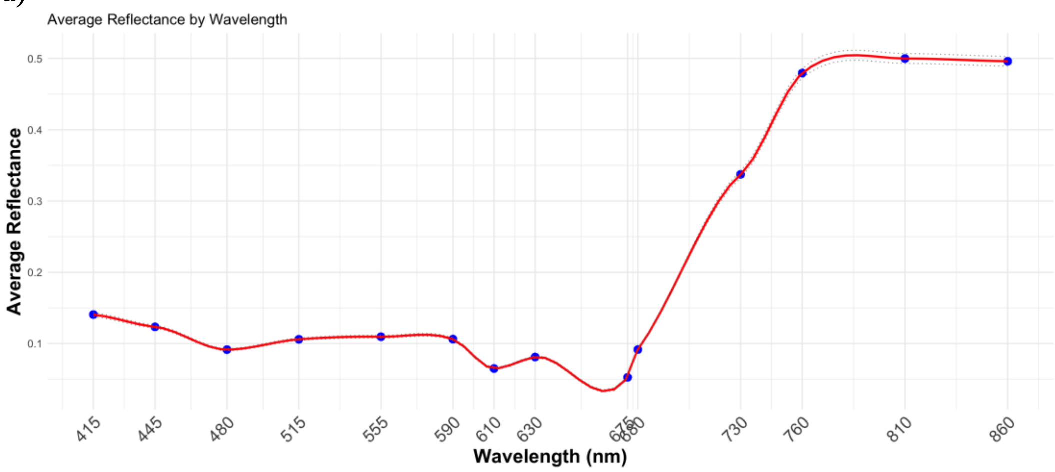
The average reflectance of the samples across wavelengths is presented in Figure 10, showing that removing unstable spectral data collected from the mobile AM3 reduced the standard deviation. Figure 11,Figure 12, Figure 13 illustrate reflectance across wavelength for all samples, respectively grouped by site, legume content, and harvest number.

Reflectance at 415 nm was higher than expected (Figure 12), due to noise. In the visible spectrum, reflectance was highest in the green region, (500-600 nm), compared to the blue (400-500 nm) and red (600-700 nm) regions, because of leaf chlorophyll. There was a steep increase in reflectance between 675 and 760 nm, followed by a plateau. While all samples followed a similar reflectance curve, greater spread between samples was seen beyond 730 nm.

Samples from Röbäcksdalen showed a higher reflectance compared to the samples from Västmanland (Figure 11). There was no apparent difference in the reflectance depending on the legume content (Figure 12) or harvest number (Figure 13), hence also time of the season. However, there may be a tendency that none or low legume content had higher reflectance.



a)



b)

Figure 10. The average spectral reflectance of all samples (red line) across wavelength (blue dots), with the average standard deviation values represented by dashed gray lines above and below. The upper plot a) is data presented before removing unstable spectral data, and the lower plot b) after removing unstable spectral data.

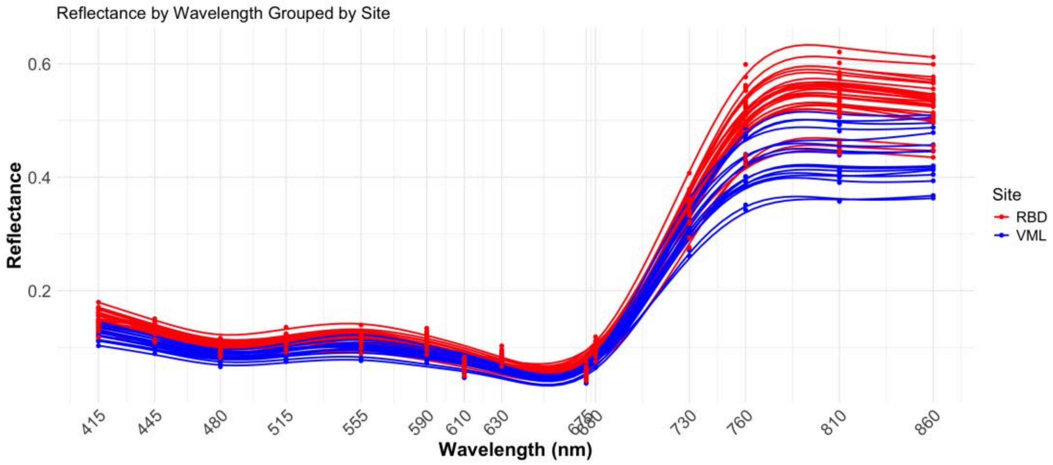


Figure 11. The reflectance across wavelength for each sample, color grouped by site. Röbäcksdalen (RBD) in red and Västmanland (VML) in blue.

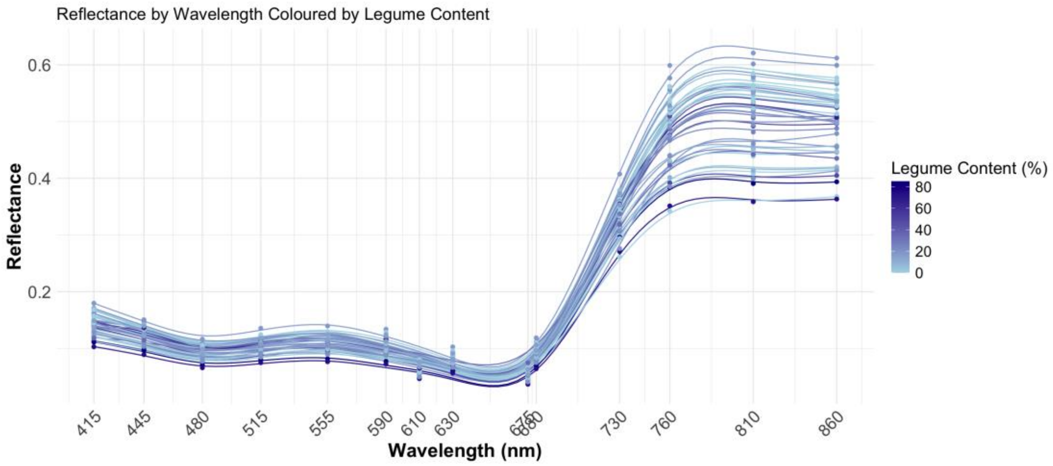


Figure 12. The reflectance across wavelength for each sample, color graduated by legume content, light blue is low legume content and dark blue is high legume content.

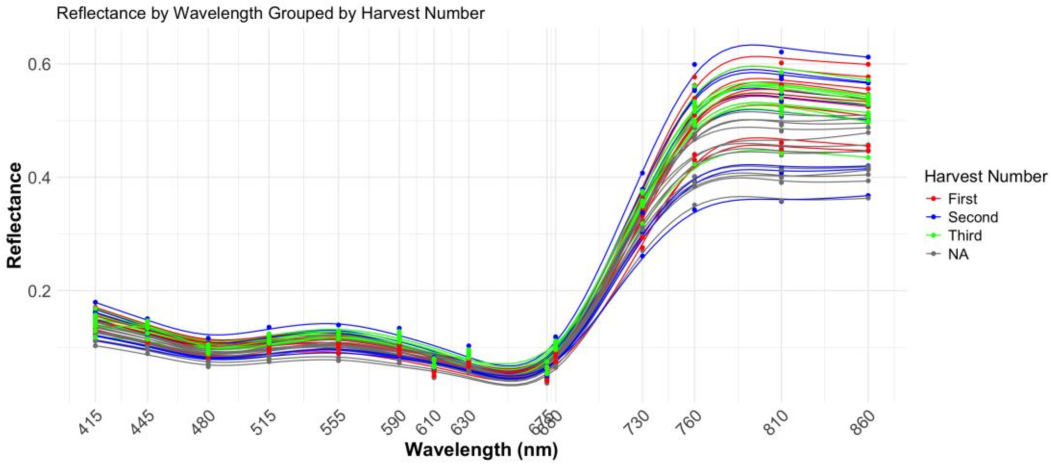


Figure 13. The reflectance across wavelengths for each sample, color grouped by harvest. First harvest in red, second harvest in green, third harvest in blue and samples with unknown harvest (N/A) in grey.

3.4 Regression models

The regression model results are presented in Table 1. MLR consistently showed the highest R^2 values. However, due to the lack of cross-validation, these results are likely affected by overfitting and are therefore excluded from further analysis.

For CP, PLS had the highest R^2 (0.68) and the lowest RMSE and RRMSE (23.6 g/kg DM, 13.8%). With wide bands, PLS had a considerable increase in R^2 (0.87) and decrease in RMSE and RRMSE (15.1 g/kg DM, 8.80%), while caretPLS and SVM saw minimal improvement.

For NDF, PLS had the highest R^2 (0.71) and the lowest RMSE and RRMSE (38.9 g/kg DM, 9.50%). Including wide bands, PLS had an increase of R^2 (0.81) and decrease in RMSE and RRMSE (32.0 g/kg DM, 7.80%), while it caused a setback for caretPLS and SVM performance.

For ME, SVM had the highest R^2 (0.67) with a slightly higher RMSE and RRMSE (0.31 MJ/kg DM, 2.90%). Including wide bands led to caretPLS ultimately achieving the best performance with a higher R^2 (0.68) than SVM with narrow bands, and the lowest RMSE and RRMSE (0.28 MJ/kg DM, 2.70%).

For OMD, caretPLS had the highest R^2 (0.59) and the lowest RMSE and RRMSE (1.84%, 2.60%). Wide bands had a negligible impact on all models.

For DM, caretPLS and SVM performed similarly, with caretPLS having a slightly higher R^2 (0.66 vs. 0.64), while SVM had a lower RMSE (2.38% vs. 2.50%) and RRMSE (11.9% vs. 13.0%). Wide bands had a negligible effect on model performance.

Table 1. Comparison of the performances of the regression models multiple linear regression (MLR), partial least square (PLS), caretPLS, and support vector machine (SVM) for the variables crude protein (CP) (g/kg DM), metabolizable energy (ME) (MJ/kg DM), neutral detergent fibre (NDF) (g/kg DM), organic matter digestibility (OMD) (%), and dry matter (DM) (g/kg DM). Performance is evaluated through root mean square error (RMSE) (same unit as variable), relative root mean square error (RRMSE) (%), and coefficient of determination (R^2). The results are divided into using only the narrow bands, to the left (nb) and both narrow and wide bands, to the right (nb + wb).

Variable	**Model**	**RMSE** nb	**RRMSE** nb	**R^2** nb	**RMSE** nb + wb	**RRMSE** nb + wb	**R^2** nb + wb
CP	MLR	22.9	13.4	0.70	13.3	7.80	0.90
CP	PLS	23.6	13.8	0.68	15.1	8.80	0.87
CP	caretPLS	30.9	18.5	0.58	32.0	19.0	0.61
CP	SVM	30.6	18.5	0.53	29.4	17.9	0.53
ME	MLR	0.24	2.20	0.69	0.18	1.70	0.82
ME	PLS	0.26	2.40	0.61	0.26	2.40	0.62
ME	caretPLS	0.30	2.80	0.65	0.28	2.70	0.68
ME	SVM	0.31	2.90	0.67	0.31	2.90	0.67
NDF	MLR	36.2	8.90	0.75	24.1	5.90	0.87
NDF	PLS	38.9	9.50	0.71	32.0	7.80	0.81
NDF	caretPLS	51.0	13.0	0.59	54.0	13.7	0.56
NDF	SVM	50.6	12.9	0.61	51.8	13.2	0.56
OMD	MLR	1.69	2.20	0.44	1.27	1.70	0.68
OMD	PLS	1.87	2.40	0.32	1.85	2.40	0.33
OMD	caretPLS	1.85	2.60	0.59	1.84	2.60	0.59
OMD	SVM	1.93	2.60	0.51	1.95	2.60	0.51
DM	MLR	2.04	9.40	0.63	1.67	7.70	0.75
DM	PLS	2.21	10.2	0.56	2.25	10.4	0.54
DM	caretPLS	2.50	13.0	0.66	2.52	13.1	0.65
DM	SVM	2.38	11.9	0.64	2.39	11.9	0.65

Importance of wavebands for prediction

All wavebands contributed to the prediction of nutritive values (Figure 14), though their significance varied across different variables and models. Overall, SVM appeared to use a broader range of wavebands compared to PLS.

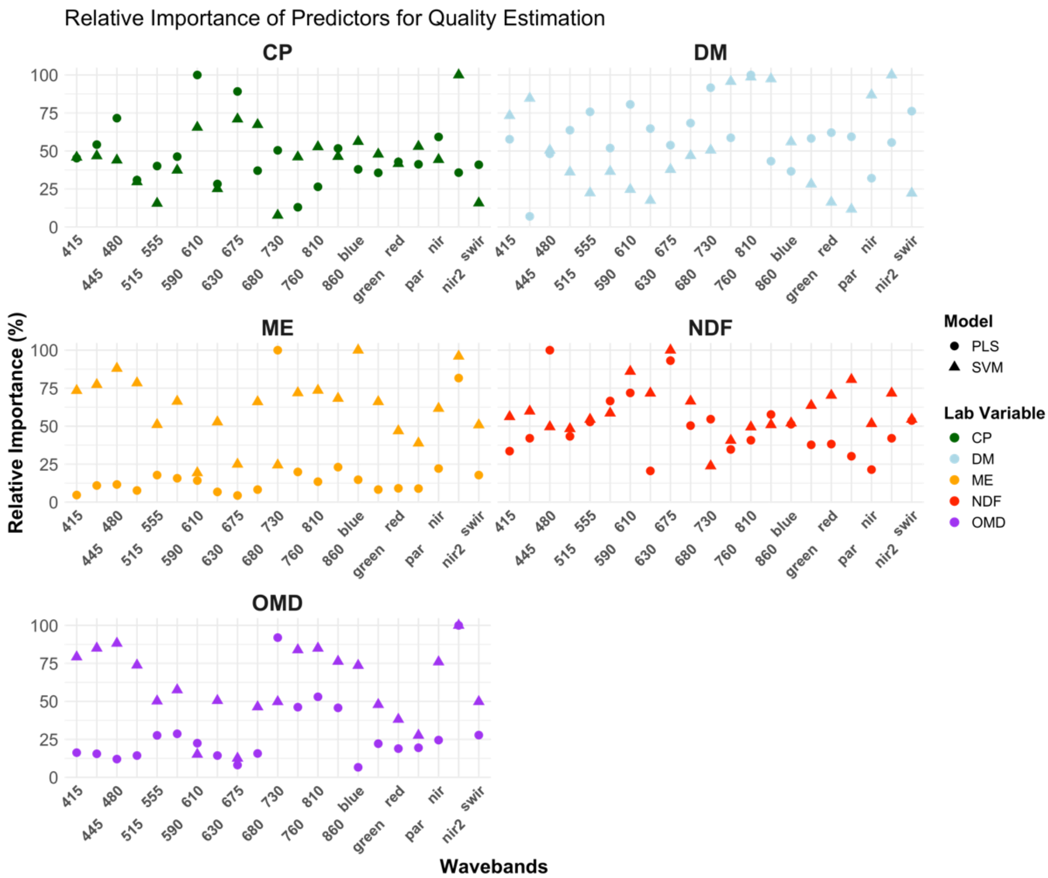


Figure 14. The relative importance of predictors (wavebands) in estimating quality parameters crude protein (CP), metabolizable energy (ME), neutral detergent fibre (NDF), organic matter digestibility (OMD), and dry matter (DM) for the regression models partial least squares (PLS) and support vector machine (SVM). The narrow wavebands included peaks at 415, 445, 480, 515, 555, 590, 610, 630, 675, 680, 730, 760, 810, and 860 nm. The wide wavebands covered spectral regions in the green, red, blue, photosynthetically active radiation (PAR), near infrared (NIR), near infrared 2 (NIR2), and short-wave infrared (SWIR) spectra.

Regression model scatter plots

Scatter plots of PLS regression models are presented in Figure 15Figure 16Figure 17Figure 18Figure 19. Scatter plots for all models are found in the appendix. Factors such as site, legume content, and harvest number seemed not to impact the predictive capacity of AM3. The scatter plots also revealed general trends, like higher legume content being associated with higher CP, and a tendency for lower ME and NDF. Additionally, ME were generally higher in the first harvests.

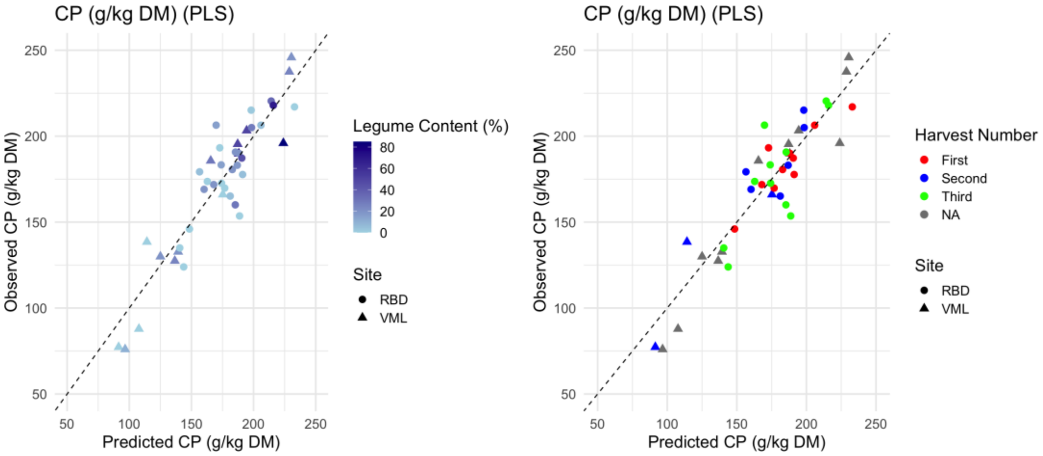


Figure 15. Predicted vs. observed crude protein (CP) using partial least squares regression (PLS). The left plot represents samples with a color gradient from light blue (low legume content) to dark blue (high legume content). The right plot groups samples by harvest number, with unknown harvest numbers labeled as "N/A." Triangles indicate samples from Röbäcksdalen (RBD), while circles represent samples from Västmanland (VML).

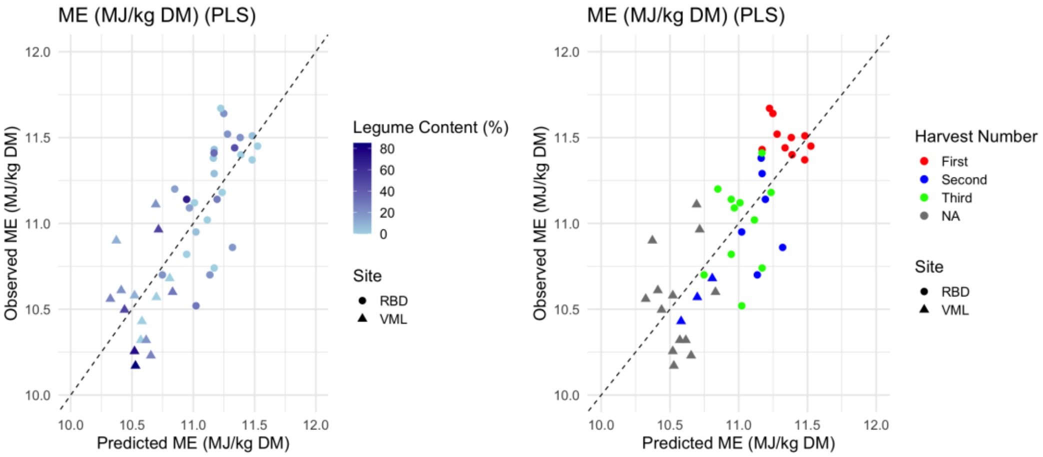


Figure 16. Predicted vs. observed metabolizable energy (ME) using partial least squares regression (PLS). The left plot represents samples with a color gradient from light blue (low legume content) to dark blue (high legume content). The right plot groups samples by harvest number, with unknown harvest numbers labeled as "N/A." Triangles indicate samples from Röbäcksdalen (RBD), while circles represent samples from Västmanland (VML).

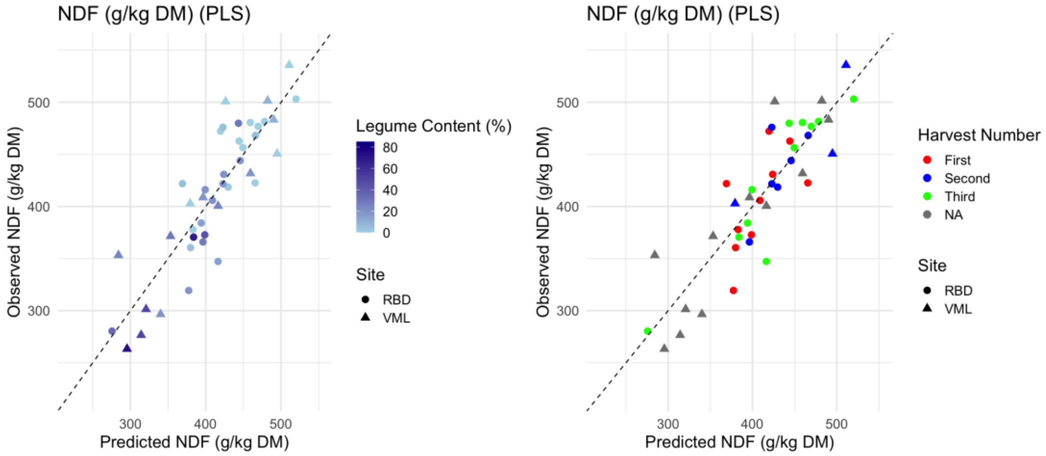


Figure 17. Predicted vs. observed neutral detergent fibre (NDF) using partial least squares regression (PLS). The left plot represents samples with a color gradient from light blue (low legume content) to dark blue (high legume content). The right plot groups samples by harvest number, with unknown harvest numbers labeled as "N/A." Triangles indicate samples from Röbäcksdalen (RBD), while circles represent samples from Västmanland (VML).

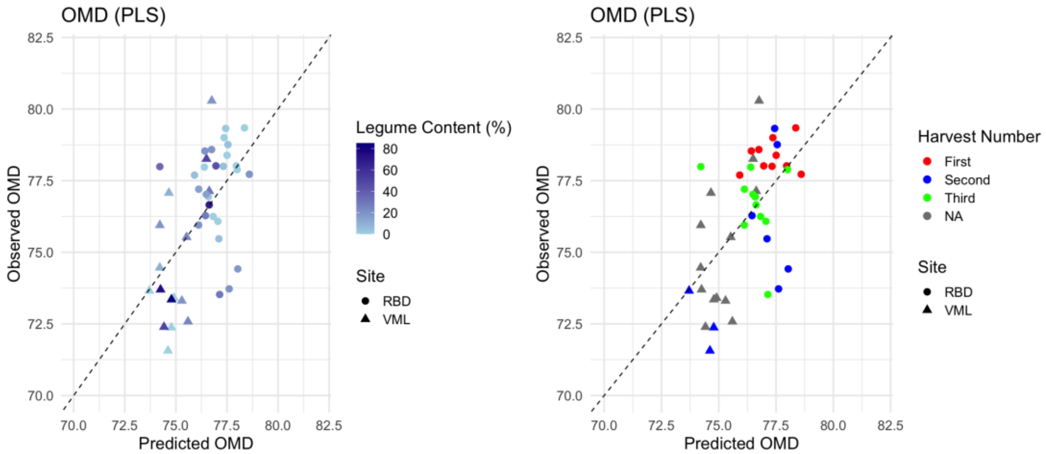


Figure 18. Predicted vs. observed organic matter digestibility (OMD) using partial least squares regression (PLS). The left plot represents samples with a color gradient from light blue (low legume content) to dark blue (high legume content). The right plot groups samples by harvest number, with unknown harvest numbers labeled as "N/A." Triangles indicate samples from Röbäcksdalen (RBD), while circles represent samples from Västmanland (VML).

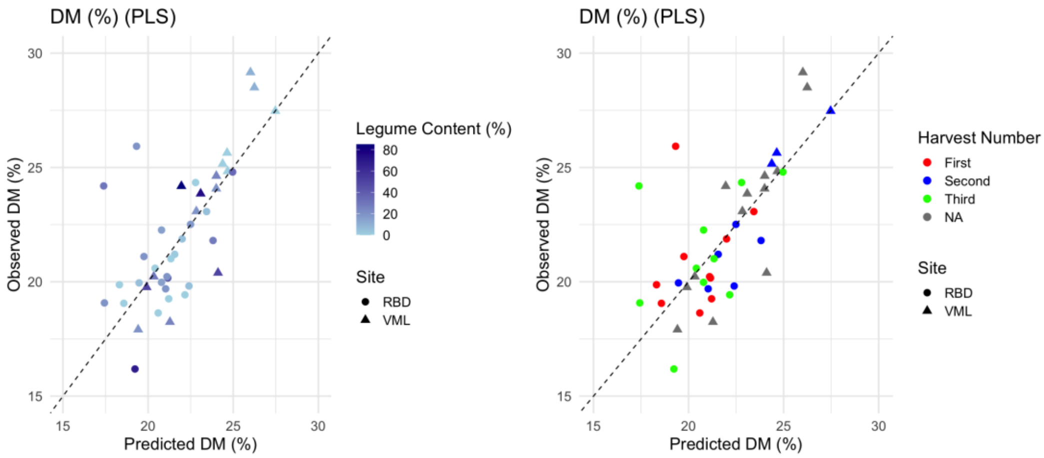


Figure 19. Predicted vs. observed dry matter (DM) using partial least squares regression (PLS). The left plot represents samples with a color gradient from light blue (low legume content) to dark blue (high legume content). The right plot groups samples by harvest number, with unknown harvest numbers labeled as "N/A." Triangles indicate samples from Röbäcksdalen (RBD), while circles represent samples from Västmanland (VML).

3.4.1 Addition of NDVI and CI as auxiliary predictors

Addition of auxiliary predictors NDVI and CI generally improved predictive model performance (Table 2), though the improvement varied across quality parameters and models. The improvements were biggest for ME, OMD and DM.

As in previous analyses, PLS remained the best-performing model for CP and NDF (despite a decrease in accuracy) but also performed best for DM with an R^2 of 0.76, 0.79, and 0.76 respectively. For OMD, caretPLS continued to be the best model, improving its R^2 to 0.75. For ME, SVM regained its position as the best model, increasing its R^2 to 0.82.

Table 2. NDVI and CI added as auxiliary predictors to the predictive models multiple linear regression (MLR), partial least squares (PLS), caretPLS, and caret support vector machine (caretSVM) using both narrow and wide bands to predict crude protein (CP) (g/kg DM), metabolizable energy (ME) (MJ/kg DM), neutral detergent fibre (NDF) (g/kg DM), organic matter digestibility (OMD) (%), and dry matter (DM) (%). Performance is evaluated by root mean square error (RMSE) (same unit as variable), relative root mean square error (RRMSE) (%) and coefficient of determination (R^2). To the right of RMSE, RRMSE, and R^2 is the change from using narrow and wide bands only.

Variable	**Model**	**RMSE**	**ΔRMSE**	**RRMSE**	**ΔRRMSE**	**R^2**	**ΔR^2**
CP	MLR	11.1	-2.28	6.70	-1.10	0.93	0.03
CP	PLS	21.0	5.91	12.8	4.00	0.76	-0.11
CP	caretPLS	34.9	2.92	14.0	-5.00	0.74	0.13
CP	SVM	34.7	5.37	16.9	-1.00	0.65	0.12
ME	MLR	0.09	-0.09	0.80	-0.90	0.96	0.14
ME	PLS	0.25	-0.01	2.30	-0.10	0.68	0.06
ME	caretPLS	0.26	-0.02	2.00	-0.70	0.79	0.11
ME	SVM	0.27	-0.04	1.90	-1.00	0.82	0.15
NDF	MLR	17.8	-6.33	4.30	-1.60	0.94	0.05
NDF	PLS	32.6	0.65	7.90	0.10	0.79	-0.02
NDF	caretPLS	52.6	-1.36	10.1	-3.60	0.70	0.14
NDF	SVM	54.9	3.16	8.40	-4.80	0.60	0.04
OMD	MLR	0.65	-0.62	0.90	-0.80	0.92	0.24
OMD	PLS	1.66	-0.19	2.20	-0.20	0.51	0.18
OMD	caretPLS	1.79	-0.05	2.20	-0.40	0.75	0.16
OMD	SVM	1.84	-0.11	2.30	-0.30	0.64	0.13
DM	MLR	1.03	-0.64	4.60	-3.10	0.87	0.12
DM	PLS	1.39	-0.86	6.30	-4.10	0.76	0.22
DM	caretPLS	1.81	-0.71	7.50	-5.60	0.72	0.07
DM	SVM	1.61	-0.78	6.80	-5.10	0.75	0.10

4. Discussion and conclusions

4.1 Stationary AM3 plant and weather data

The long break between June 5th and July 5th before and after first harvest was due to delays in harvesting, fertilization, and vacation, which prolonged the data gap. The impact of the first harvest was clearly visible as shown by a sharp increase in NDVI and CI, confirming regrowth (Figure 9). However, the second harvest was less distinguishable in NDVI and CI changes, as efforts were made to prevent another prolonged data gap. To achieve this, the sensor was left in place while mowing was conducted around it. Consequently, the second harvest was performed by hand in the sensors near vicinity, leading to not properly harvested ley.

How to handle harvesting and fertilization without disrupting data collection is a practical challenge when using stationary AM3 in ley fields, that must be solved. One possible solution could be to drive around the sensor during fieldwork and subsequently relocate it to a new field spot.

Despite the challenge, the weather and plant data collected by the stationary AM3 demonstrate its versatility beyond spectral reflectance measurements. By leveraging its stationary functionality, the full potential of the AM3 can be used.

4.2 Reflectance patterns from mobile AM3

The standard deviation reduced after removing the unstable spectral data from the AM3 (Figure 10), highlighting the importance of including only stable spectral measurements in data analysis. This also underscores the importance of time for spectral data collection, as up to 15 minutes of data needed to be removed. For future spectral measurements, at least half an hour of spectral data collection is recommended.

The noise observed at the beginning of the spectral pattern may have introduced confounding effects in the regression models and should be considered in future AM3 analyses.

The higher reflectance observed at Röbäcksdalen remains partially unexplained within the scope of this study. Zhou et al. (2019) found that the addition of clover and N fertilization to the ley increased chlorophyll content, which reduced reflectance in the visible range and increased leaf biomass, which increased reflectance in the NIR range. The higher reflectance of the samples from Röbäcksdalen could partly be attributed to greater N fertilization and clover content, as the difference in reflectance was lower in the visible range and higher in the NIR range. Although the samples from Röbäcksdalen did not have the highest CP, they were generally on the higher end, which supports this.

On the other hand, Zhou et al. (2019) also found that pure grass exhibited higher reflectance than mixed swards. A similar trend may be present in this study, as lower legume content appears to be associated with higher reflectance (Figure 12). However, this relationship remains unclear, and the consistently higher reflectance observed in the samples from Röbäcksdalen complicates the interpretation.

Another potential factor influencing reflectance measurements is the sensor height during data collection. The AM3 was intended to be held at 1.0 m above the plant canopy, but due to a misunderstanding, samples from Västmanland were measured at a fixed height of 1.0 m, without accounting for canopy height variations. Since the sensor in Röbäcksdalen was positioned higher to account for canopy height, it would have captured a larger surface area of the ley, potentially influencing the reflectance data.

Importantly, the difference in reflectance between sites did not appear to affect the performance of the regression models.

The heterogeneity of the ley samples in this study, such as location, species composition, management, and seasonal timing, may introduce confounding effects on the relationship between spectral reflectance and nutritive value. However, neither site, legume content, nor harvest number appeared to impact model performance.

4.3 Performance of regression models

The performance of the regression models in this study is generally similar to previous studies, both in R^2 and prediction errors (Table 3). MLR consistently showed the best performance and given its inability to handle complex datasets and lack of cross-validation, the results were likely due to overfitting (Coen et al. 2007). At the same time, MLR is a less flexible and linear model that makes it less susceptible to over-fitting.

PLS regression performed best for predicting CP and NDF (R^2 = 0.87, 0.81) and caretPLS performed best for ME, OMD and DM (R^2 = 0.68, 0.59, 0.66), including both narrow and wide bands. While the models show potential, the limited dataset size restricts the reliability of conclusions.

Sun et al. (2022) found that with the ASD FieldSpec both PLS and SVM models could successfully predict quality parameters, with SVM performing best for CP (R^2 = 0.71) and PLS being more robust in estimating NDF and digestibility (IVTD) (R^2 = 0.87, 0.73). Duranovich et al. (2020) only tested PLS and achieved R^2 values between 0.55 to 0.77 for CP, ME, NDF, and digestibility (DOMD) with ASD Fieldspec. Fernández-Habas et al. (2022) also did not test SVM and achieved PLS R^2 values from 0.59 to 0.84 for CP, NDF, and digestibility (EDOM) using selected spectral bands from the ASD Fieldspec.

Morel et al. (2022) also observed comparable performance between PLS and SVM with the Yara N-sensor. They concluded that PLS performed best for NDF and digestibility (IVTD) (R^2 = 0.78, 0.64), while SVM was best for CP (R^2 = 0.49). In contrast Zhou et al. (2019) reported much higher SVM R^2 values (0.84) compared to PLS (0.68) from the Yara N-sensor in estimating CP concentration. A distinguishing feature of the study of Zhou et al (2019) was the inclusion of all available data from sample sites. Perhaps SVM was able to handle nonlinear relationships and separating overlapping data points better, using its kernel trick (Mountrakis et al.2011), but also risking overfitting (Coen et al. 2007).

Table 3. Comparison of results from recent similar studies using field spectrometers and partial least square (PLS) or support vector machine (SVM) to predict ley quality. Besides Arable Mark 3 (AM3), either Yara N-sensor (YNS) or ASD Fieldspec (ASD FS). The quality parameters include crude protein (CP) (g/kg DM), metabolizable energy (ME) (MJ/kg DM), neutral detergent fibre (NDF) (g/kg DM*), in vitro true digestibility (IVTD) (g/kg DM), organic matter digestibility (OMD) (%), digestible organic matter in dry matter (DOMD) (% of DM), and enzyme digestibility of organic matter (EDOM) (% of DM). Performance is evaluated by relative root mean square error (RRMSE) (%) and coefficient of determination (R^2). N/A indicates missing values. *if not stated otherwise.*

Study	Sensor	Variable	Model	RRMSE	R^2
This study	**AM3**	**CP**	**PLS**	**9.20**	**0.87**
Zhou et al. (2019)	YNS	CP (% of DM)	SVM	N/A	0.84
Morel et al. (2022)	YNS	CP	PLS	13.0	0.49
Sun et al. (2022)	ASD FS	CP	SVM	10.0	0.71
Duranovich et al. (2020)	ASD FS	CP (% of DM)	PLS	11.7	0.77
Fernández-Habas et al. (2022)	ASD FS	CP (% of DM)	PLS	N/A	0.84
This study	**AM3**	**ME**	**caretPLS**	**2.90**	**0.68**
Duranovich et al. (2020)	ASD FS	ME	PLS	4.88	0.59
This study	**AM3**	**NDF**	**PLS**	**8.30**	**0.81**
Sun et al. (2022)	ASD FS	NDF	PLS	7.77	0.85
Morel et al. (2022)	YNS	NDF	PLS	8.00	0.78
Duranovich et al. (2020)	ASD FS	NDF (% of DM)	PLS	7.96	0.55
Fernández -Habas et al. (2022)	ASD FS	NDF (% of DM)	PLS	N/A	0.67
This study	**AM3**	**OMD**	**caretPLS**	**2.60**	**0.59**
Sun et al. (2022)	ASD FS	IVTD	PLS	2.01	0.73
Morel et al. (2022)	YNS	IVTD	PLS	2.10	0.64
Duranovich et al. (2020)	ASD FS	DOMD	PLS	2.47	0.58
Fernández -Habas et al. (2022)	ASD FS	EDOM	PLS	N/A	0.59

Addition of NDVI and CI

The addition of auxiliary predictors NDVI and CI led to big improvements in regression model performances for ME, OMD, and DM (R^2 = 0.76, 0.79, and 0.76) especially for SVM (Table 2). The underlying reason for this improvement remains unclear. A reason could be due to differences between measurement occasions such as imperfect calibration or differing weather conditions is partially canceled out in indices compared to waveband reflectance values. In addition, the indices are designed to capture the important information in the reflectance spectrum, that correlates with crop properties. On the other hand, NDVI and CI are calculated based on NIR and red bands (Arable 2022). Since they originate from spectral data this may lead to correlated and overlapping data, which risks overfitting

(Mountrakis et al. 2011; Coen et al. 2007). Future research should investigate the potential of adding indices and the risk of overfitting.

Importance of predictors

The AM3 primarily operated in the visible and red edge spectral regions, with limited sensitivity beyond 910 nm (Figure 6). Sun et al. (2022) highlighted the importance of the visible spectrum for predicting ley quality, which can explain the relatively good result achieved in this study. However, Oliveira et al. (2023) identified the SWIR region (1050 to 1700 nm) as important for estimating NDF and CP, due to a high sensitivity for lignin, cellulose, and N in this region. This could explain big improvement in regression model performance, for CP and NDF, when including wide bands which included a SWIR band.

All wavebands contributed to the prediction in the regression models, highlighting the value of using multiple wavebands in a spectrometer. This aligns with Sun et al. (2022), who found that selecting only the most sensitive wavelengths did not enhance regression model performance. However, Fernández-Habas et al. (2022) showed that applying the backward feature elimination (BFE) technique to identify the most important narrow bands enhanced PLS performance. BFE led to better handling of overlapping data points and the removal of redundant spectral information. A method which could be tested in future studies as it can improve PLS performance and decrease risk of overfitting with SVM.

The results suggest that no single approach works best for all ley quality parameters and models. Including wide bands to the narrow bands gave big improvements for PLS in predicting NDF and CP but had barely any effect on caretPLS and SVM in predicting ME, OMD, and DM. Adding NDVI and CI gave considerable improvements for all models except for PLS which decreased in predicting CP and NDF. This indicates that ley quality estimation with the AM3 requires tailored approaches for each ley quality parameter, rather than a one-size-fits-all solution.

4.4 Future directions for further studies with the AM3

A larger and more diverse dataset is required, as the reliability of both machine learning algorithms and statistical methods heavily relies on the size and representativeness of the input data (Morel et al. 2022). Previous studies have used datasets of varying sizes to achieve robust model performance. For example, Zhou et al. (2019) worked with 377 samples, using 251 for calibration and 125 for validation. Similarly, Sun et al. (2022) used a total of 235 samples divided into 157 for calibration and 78 for validation. Morel et al. (2022) used 336 samples. Duranovich et al. (2020) collected 272 samples, with 20% used for validation, and Fernández-Habas et al. (2022) had 173 samples, validating with 30% of the dataset.

While these datasets were deemed sufficient for their respective projects, all studies emphasized the need for further data collection, especially for studies like Morel et al. (2022), which were restricted to one location and a single ley type.

For further data collection with the AM3, two approaches could be considered: making it more simple or complex. Some field observations recorded were not used in the analysis and could be removed. Or even more variables could be included which may enhance regression model performance. For example, Sun et al. (2022) found that incorporating crop height as an auxiliary variable improved model predictive performance compared to spectral data alone, suggesting a possible additional data input for the AM3 as well.

A practical alternative is to use variables already measured by the AM3, such as NDVI and CI, as was tested in this project. The AM3 measures much more variables than those used in this study, that could be added. Future research should explore the integration of these additional variables, while also assessing the trade-offs between model performance and model complexity and the risk of overfitting.

4.5 Applicability to farmers and advisors

Lantmännen (2021) emphasize the importance of on-farm technical solutions that provide real-time data for decision making for improved ley production. The AM3 shows good potential to deliver this in the future. Additionally, the cost of implementing the AM3 is relatively low, helping to overcome the financial barriers often associated with adopting new technology (Lantmännen 2021; Villa-Henriksen 2020; Schellberg et al. 2008). However, lot of data collection and refinement are required before a robust and reliable AM3-based decision support system for ley harvest timing can be developed. The development should be focused on the farmer as the end user, ensuring practicality and easy adoption (Nettle et al. 2022). The AM3 is user-friendly, but automation is needed to deliver quality parameters directly to the farmer in a simplified format, similar to a traditional feed analysis report.

Adding more predictive variables may improve model performance but also increase complexity, which could hinder practical application. Farmers already face administrative burdens, and tools that require a lot of data input might discourage adoption. The success of simple decision support systems like Vallprognos underscores the importance of keeping tools simple. Maintaining a straightforward approach will help the model deliver valuable insights while remaining practical. However, could much data of interest, such as field history and fertilization rates, already be documented. This raises the question of data availability and accessibility, as identified by Lantmännen (2021), Villa-Henriksen (2020), and Schellberg et al. (2008). If advisors or external systems could access and integrate relevant field data, it would reduce burden on farmers, making the tool easier to adopt.

Dream scenario with the AM3

The mobile use of the AM3 was primarily intended for data collection from multiple fields, but this approach is time consuming and does not reflect how a typical farmer would use it. Instead, farmers would benefit more from using the AM3 as a stationary device, deployed in the field throughout the growing season. This minimizes setup time, requiring only removal and reinstallation during harvesting and fertilization. It would allow continuous monitoring of quality parameters and their relationship to weather data, such as growing degree days, enabling a more comprehensive dataset, without additional work, specific to field conditions.

The ideal way to use the AM3 would be to deploy it in the beginning of the growing season in representative and early ley field to collect weather and plant data. If an automated decision support system is developed, the AM3 could provide real-time ley quality estimations, allowing farmers to monitor plant development remotely. When it is time to harvest, the sensor would be removed and placed in another field, using its mobile capacity, allowing farmers to compare field development and plan accordingly. Another use could be to monitor the drying process for ensiling, measuring DM (and WSC, which should be considered in future studies). Once harvest is complete, the AM3 could be reinstalled in the original field. Additionally, this method could possibly monitor plant biomass, enabling farmer to track trade-offs between yield and quality.

The mobile use of the AM3 could serve as a tool for agricultural advisors, particularly before a fully automated decision support system is developed. In this transitional phase, advisors could manage tedious data inputs and calculations. This could also help introduce the AM3 into farmer application, as advisors can play a key role in educating farmers and facilitating experience with new technology. Nettle et al. (2022) emphasize joint, personal engagement of technology developers, scientists, advisors and farmers in exploration in implementing new agricultural technologies as an effective strategy.

What is accurate enough for practical use?

The residual predictive deviation (RPD) value assesses how well a model can predict new unseen data relative to the variation in the dataset (Cozzolino et al. 2006). RPD values above 3.0 are considered accurate enough for laboratory-based NIRS analysis for agricultural products. In field conditions, measurement variability lowers prediction accuracy, meaning that even lower RPD values can still indicate good performance. According to Terhoeven-Urselmans et al. (2006), an RPD between 1.4 and 2.0 is considered good, while values above 2.0 are very good.

RPD values with the ASD Fieldspec for estimating ley quality was reported by Biewer et al. (2009) for CP = 2.7 and ME = 1.9 and Duranovich et al. (2020) and Fernández-Habas et al. (2022) for and for CP, ME, NDF and digestibility ranging from 1.46 to 1.84 and 1.55 to 2.47 respectively. In further model development for the AM3, the RPD could be calculated as a benchmark for predictive accuracy.

Prediction performance can also be assessed through RMSE. For example, the respective RMSE for CP, ME and NDF was 15.1 g/kg DM, 0.28 MJ/kg DM, and 32.0 g/kg DM (Table 1). Ultimately, it is up to the farmer to determine whether this level of accuracy meets their needs. Additionally, if the AM3 is deployed stationary, the change of time may provide valuable insights, even if individual predictions have some variability.

4.6 Conclusions

- The AM3 showed good potential for estimating ley quality. However, extensive diverse data collection is required to expand the training dataset and develop reliable predictive models.
- PLS regression performed best for predicting CP and NDF (R^2 = 0.87, 0.81) and caretPLS performed best for ME, OMD and DM (R^2 = 0.68, 0.59, 0.66).
- Leveraging auxiliary variables already measured by the AM3 can enhance model performance, but the risk of overfitting must be evaluated.
- Legume content, location, and harvest number did not appear to affect the performance of the regression models developed from AM3 spectral data, suggesting robustness across different conditions.
- For future data collection, ensure height of the spectrometer is fixed from the canopy, and spectral data should be collected for at least half an hour. Practical challenges related to stationary AM3 placement during field management need to be solved.
- Simplicity versus complexity need to be considered when moving forward with data collection and model development. While adding more predictors in the regression models may improve accuracy, it also increases complexity and can in the end hinder farmer adoption.
- Involve farmers and advisors in developing the decision support system to strengthen the applicability of the AM3.

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Popular science summary

Ley is the biggest crop in Sweden and forms the foundation of diets for cows, sheep, and horses. Cultivating ley offers many benefits, such as carbon sequestration and increased yield for subsequent crops. Improving the ley quality is necessary for increasing the proportion of forage in livestock diets, which benefits the environment by reducing reliance on imported feed and promotes soil health. It also provides economic advantages for farmers by lowering feed costs and increasing livestock productivity.

A critical factor in achieving high-quality ley is harvesting at the right time. However, balancing high yields with good nutritive value is challenging. As plants grow, yields increase, but quality declines, structural fibres, necessary for plant support, reduce the levels of protein and energy. Currently, farmers lack a reliable decision support system to guide them through quality changes in ley across the harvests of the growing season.

This study evaluated the potential of the Arable Mark 3 (AM3), an affordable and user-friendly field spectrometer, as a decision support tool for farmers. Among its functions, the AM3 measures light reflected by crops, with reflected light corresponding to specific plant attributes. For example, crude protein can be estimated because it contains nitrogen, which is abundant in chlorophyll. Chlorophyll absorbs light in the red spectrum, making plants appear green, and the amount of light reflected in this spectrum can indicate the protein content. Similar relationships may exist for other nutritional values, such as energy content. This study tested whether the AM3 could reliably predict ley quality based on spectral measurements.

To investigate this, ley samples were first measured using the AM3, then harvested and analyzed in the laboratory for nutritional values. Statistical models were used to identify relationships between the AM3's spectral data and lab results. Among the tested models, two types of partial least squares (PLS and caretPLS) performed best for protein, energy, fibre, digestibility, and dry matter. Including additional data, such as vegetation indices and other plant measurements already available from the AM3, further improved prediction accuracy. The results showed that the AM3 performed well. Its prediction accuracy was comparable to more expensive tools used in research. However, a lot more data collection is necessary to develop reliable and robust models.

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Appendix

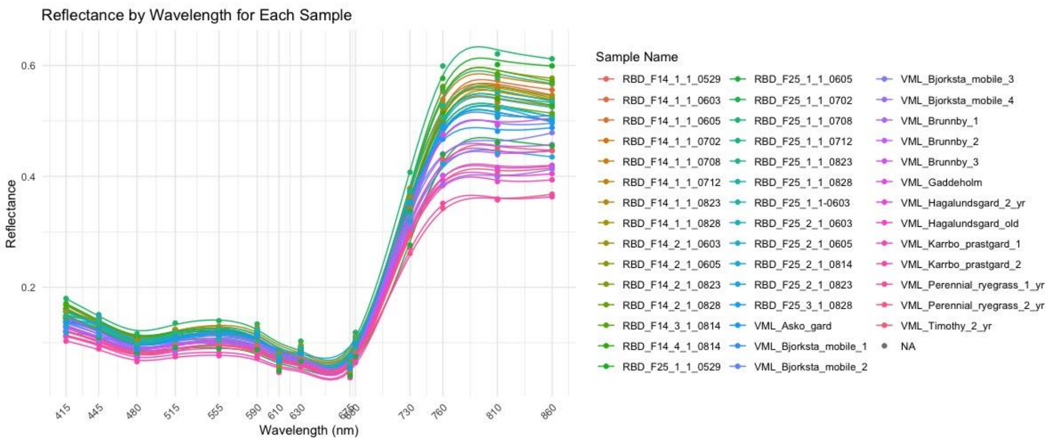

Figure 20. The reflectance across wavelengths plotted for each sample, with colors corresponding to the sample names listed on the right.

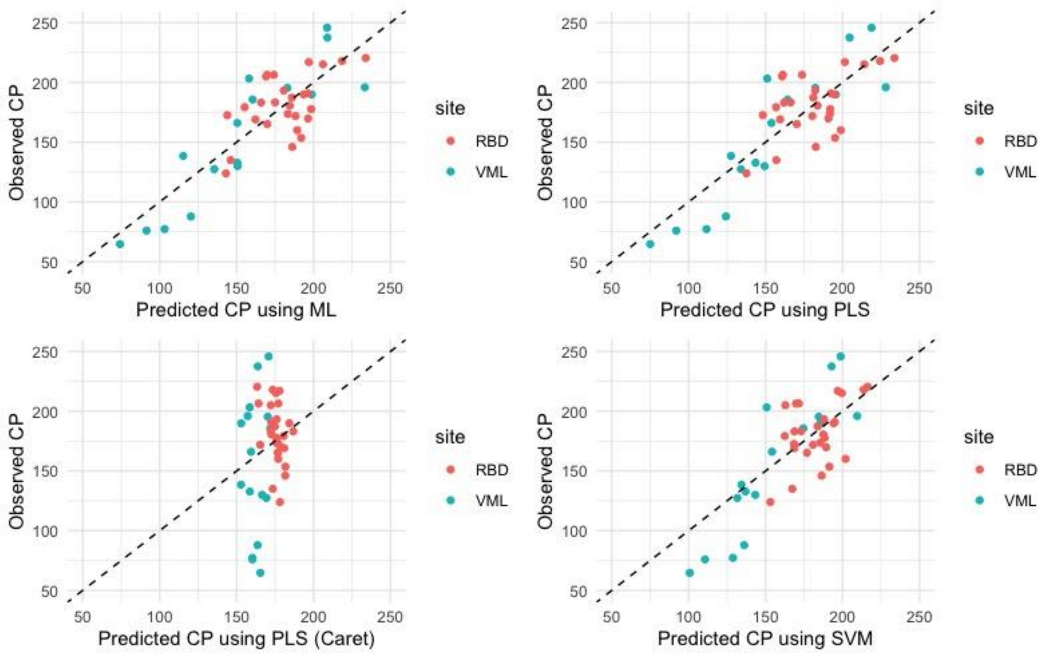

Figure 21. Predicted vs. observed crude protein (CP) (g/kg DM) for multiple linear regression (MLR), partial least squares (PLS), PLScaret, and support vector machine (SVM). Data points are color-coded by site, red for Röbäcksdalen (RBD) and blue for Västmanland (VML).

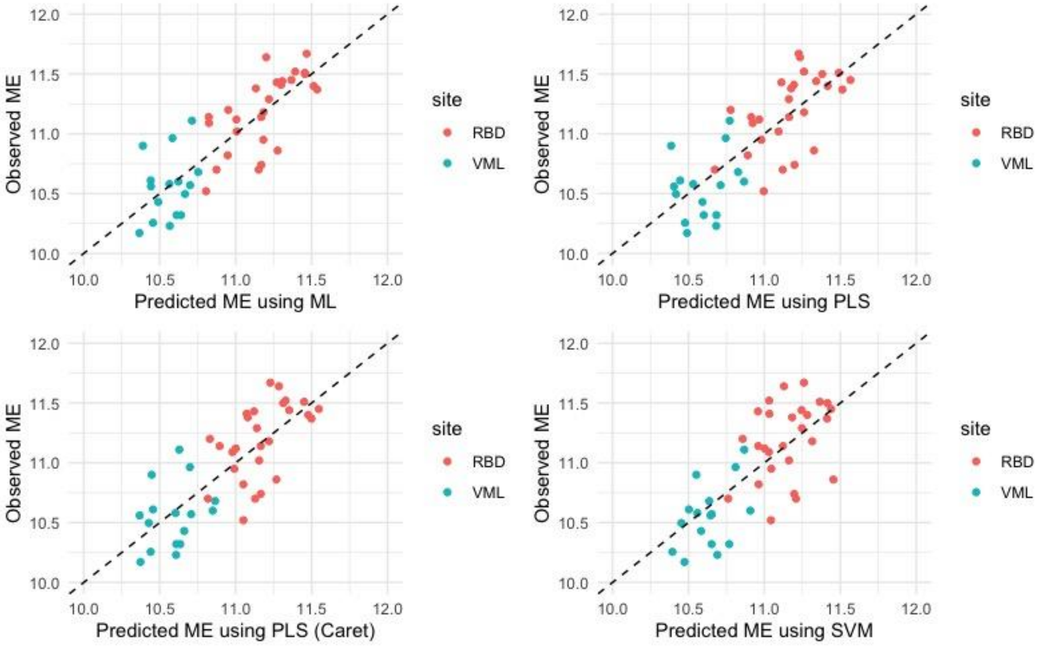

Figure 22. Predicted vs. observed metabolizable energy (ME) (MJ/kg DM) for multiple linear regression (MLR), partial least squares (PLS), PLScaret, and support vector machine (SVM). Data points are color-coded by site, Röbäcksdalen (RBD) and blue for Västmanland (VML).

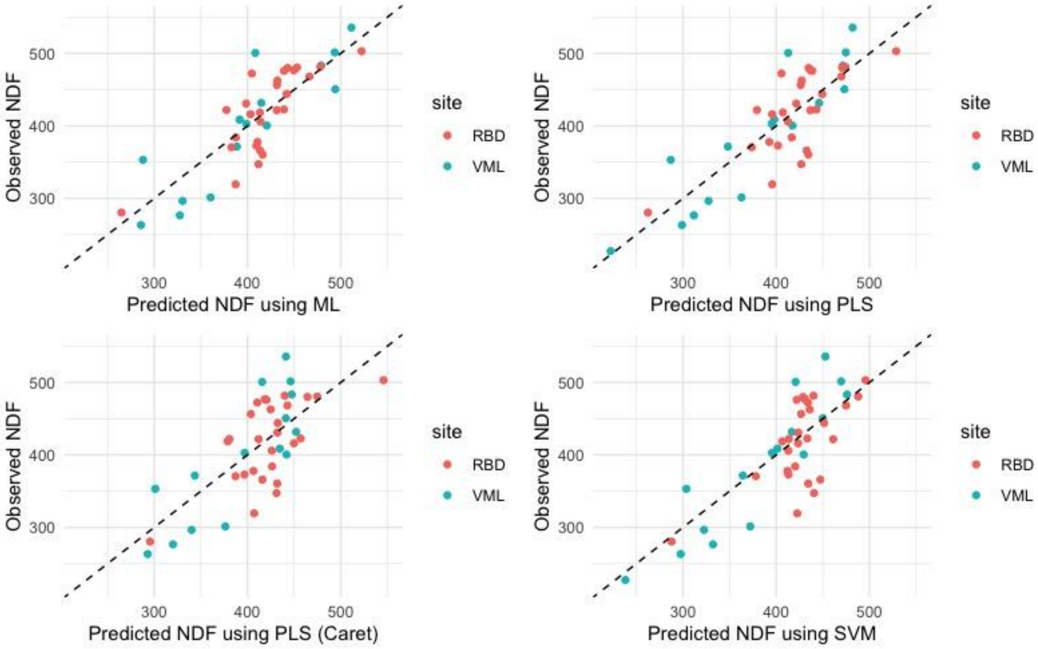

Figure 23. Predicted vs. observed neutral detergent fibre (NDF) (g/kg DM) for multiple linear regression (MLR), partial least squares (PLS), PLScaret, and support vector machine (SVM). Data points are color-coded by site, Röbäcksdalen (RBD) and blue for Västmanland (VML).

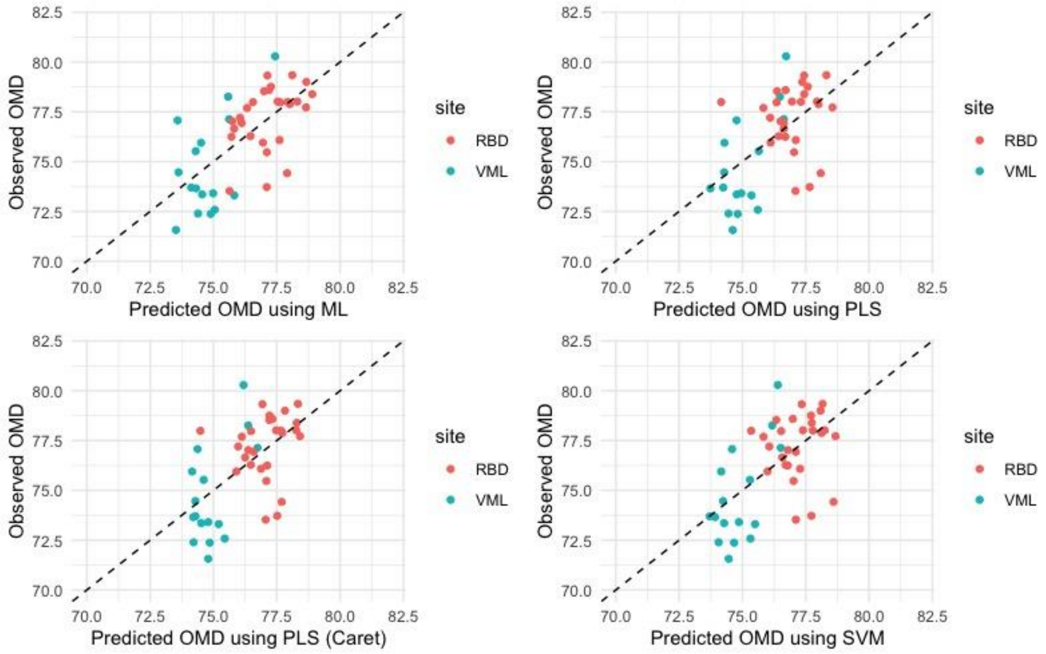

Figure 24. Predicted vs. observed organic matter digestibility (OMD) (%) for multiple linear regression (MLR), partial least squares (PLS), PLScaret, and support vector machine (SVM). Data points are color-coded by site, Röbäcksdalen (RBD) and blue for Västmanland (VML).

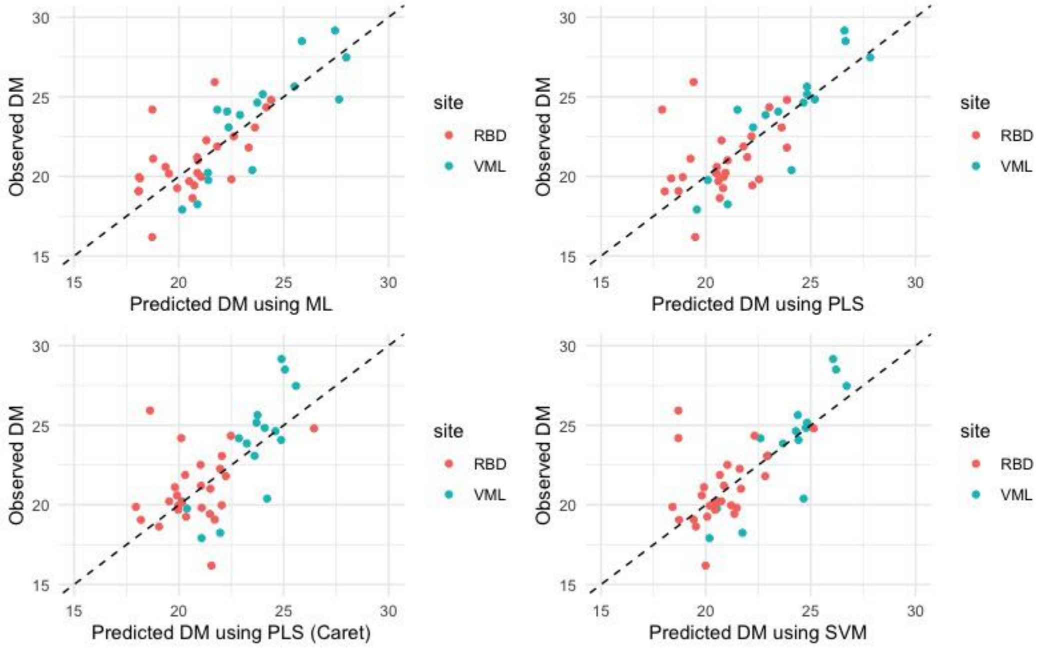

Figure 25. Predicted vs. observed dry matter (DM) (%) for multiple linear regression (MLR), partial least squares (PLS), PLScaret, and support vector machine (SVM). Data points are color-coded by site, Röbäcksdalen (RBD) and blue for Västmanland (VML).

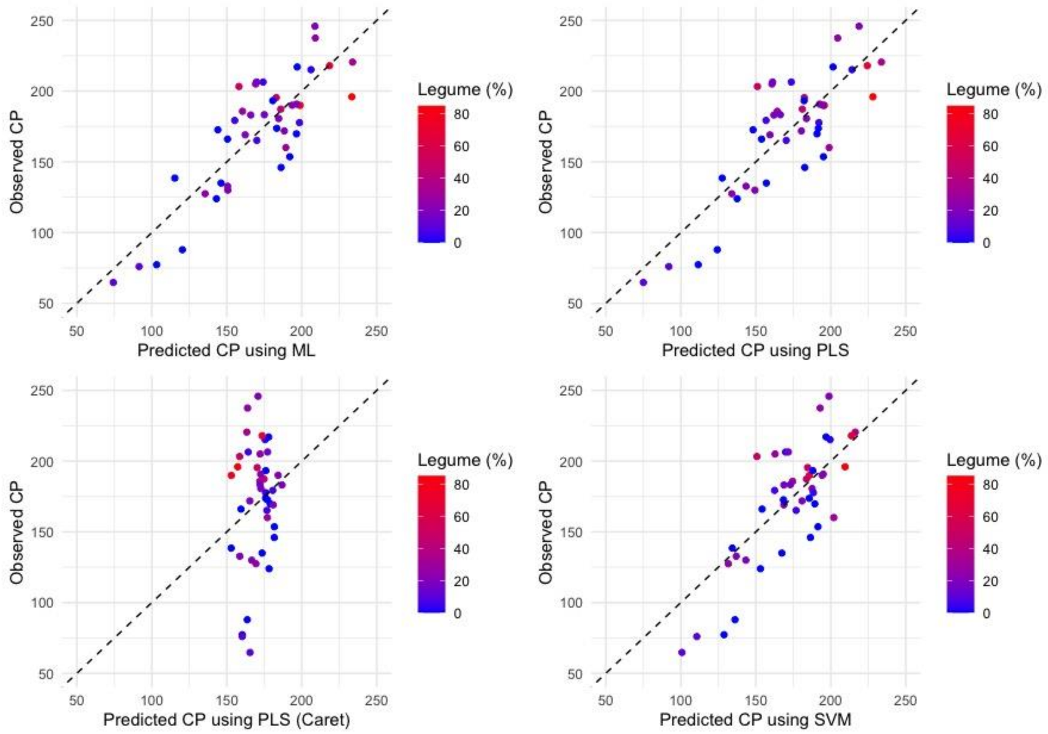

Figure 26. Predicted vs. observed crude protein (CP) (g/kg DM) for multiple linear regression (MLR), partial least squares (PLS), PLScaret, and support vector machine (SVM). Data points are color-gradiented by legume content (%), red for high and blue for low.

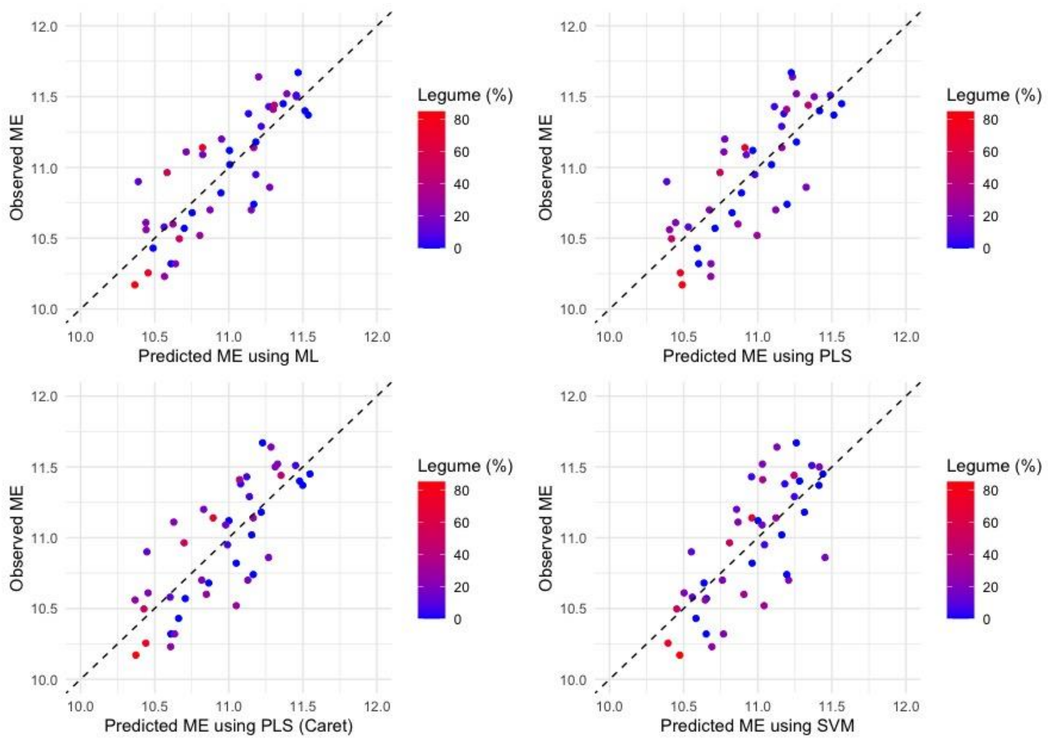

Figure 27. Predicted vs. observed metabolizable energy (ME) (MJ/kg DM) for multiple linear regression (MLR), partial least squares (PLS), PLScaret, and support vector machine (SVM). Data points are color-gradiented by legume content (%), red for high and blue for low.

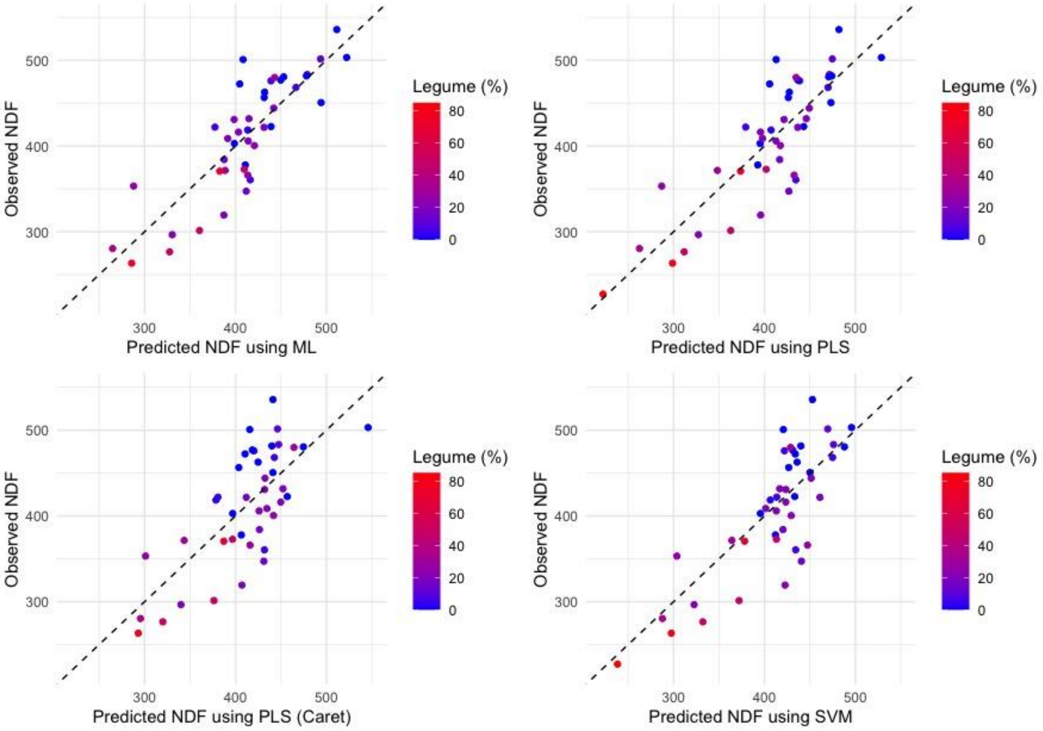

Figure 28. Predicted vs. observed neutral detergent fibre (NDF) (g/kg DM) for multiple linear regression (MLR), partial least squares (PLS), PLScaret, and support vector machine (SVM). Data points are color-gradiented by legume content (%), red for high and blue for low.

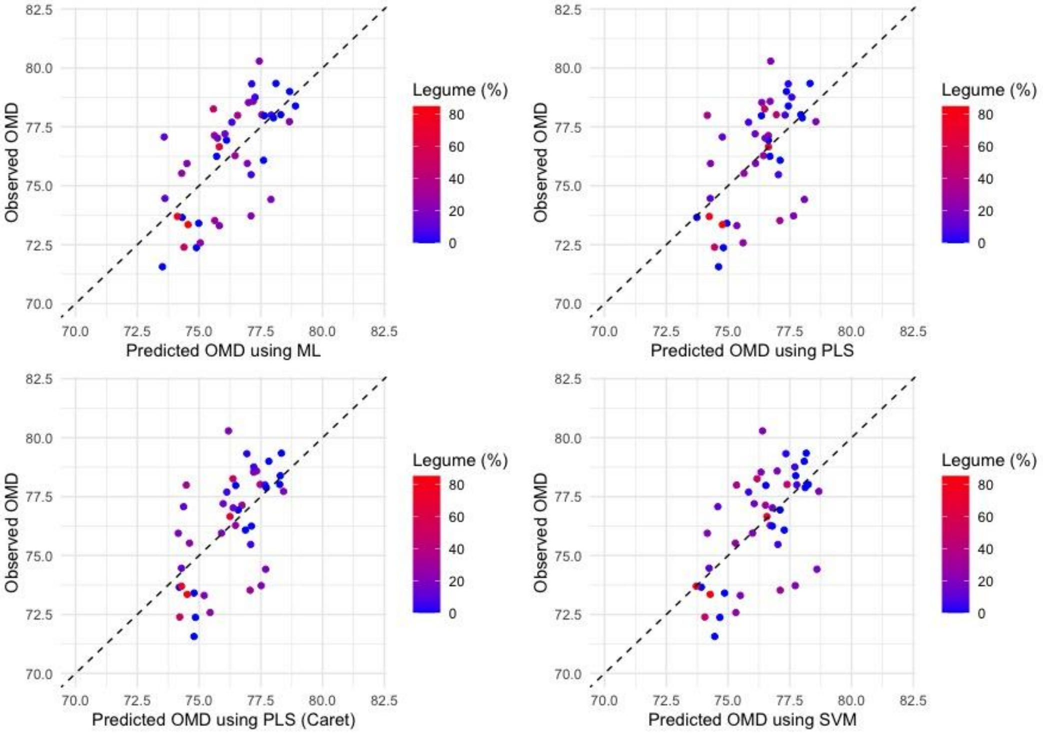

Figure 29. Predicted vs. observed organic matter digestibility (OMD) (%) for multiple linear regression (MLR), partial least squares (PLS), PLScaret, and support vector machine (SVM). Data points are color-gradiented by legume content (%), red for high and blue for low.

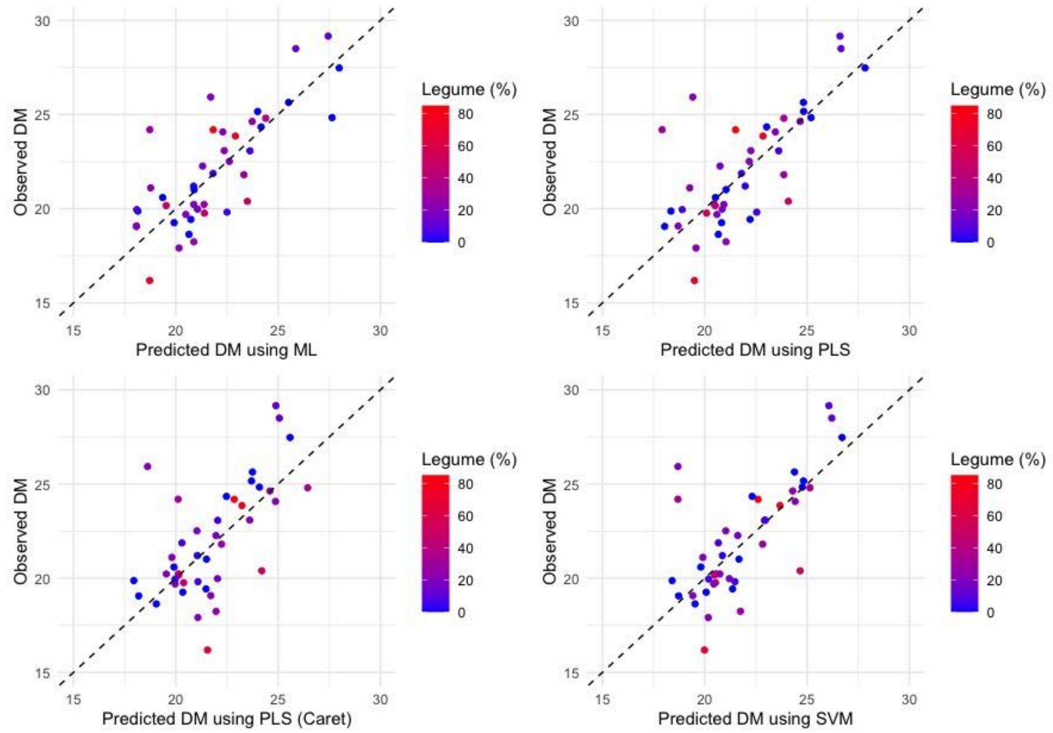

Figure 30. Predicted vs. observed dry matter (DM) (%) for multiple linear regression (MLR), partial least squares (PLS), PLScaret, and support vector machine (SVM). Data points are color-gradiented by legume content (%), red for high and blue for low.

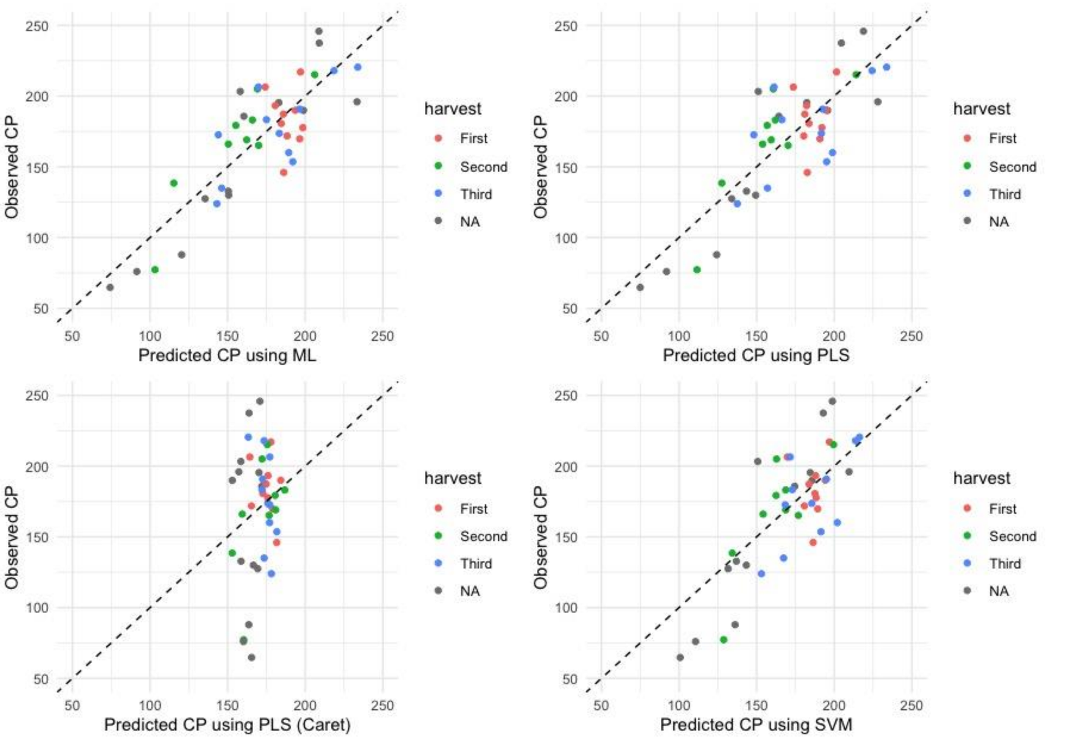

Figure 31. Predicted vs. observed crude protein (CP) (g/kg DM) for multiple linear regression (MLR), partial least squares (PLS), PLScaret, and support vector machine (SVM). Data points are color-coded by site, red for first, green for second, blue for third, and grey for unkown (N/A).

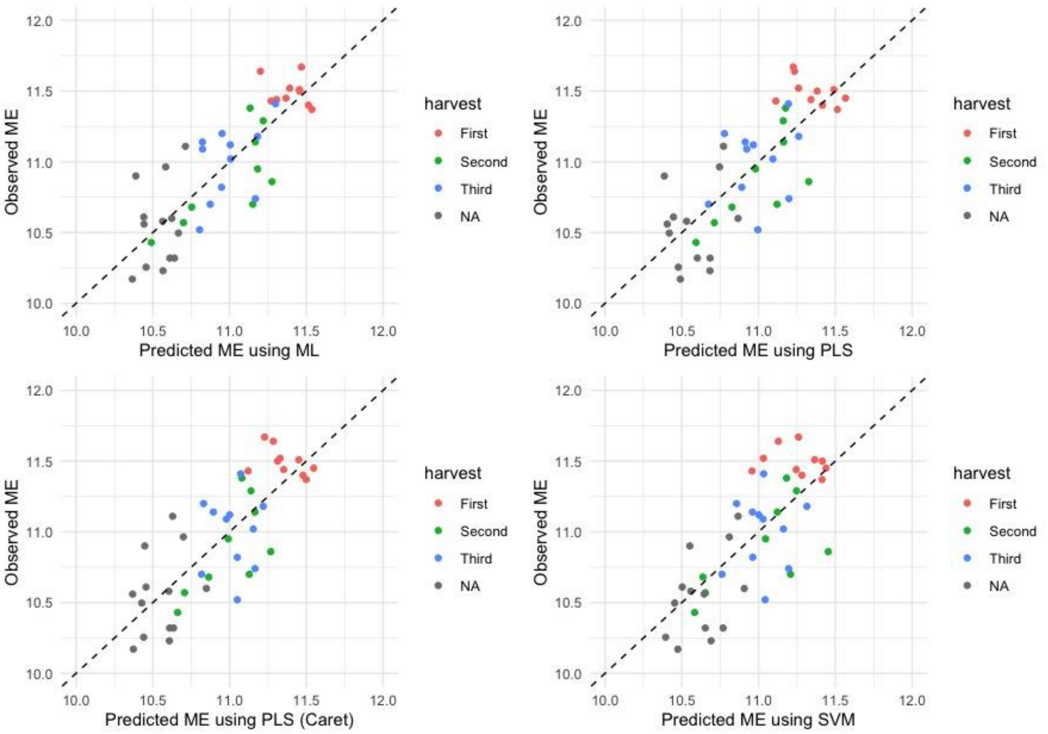

Figure 32. Predicted vs. observed metabolizable energy (ME) (MJ/kg DM) for multiple linear regression (MLR), partial least squares (PLS), PLScaret, and support vector machine (SVM). Data points are color-coded by site, red for first, green for second, blue for third, and grey for unkown (N/A).

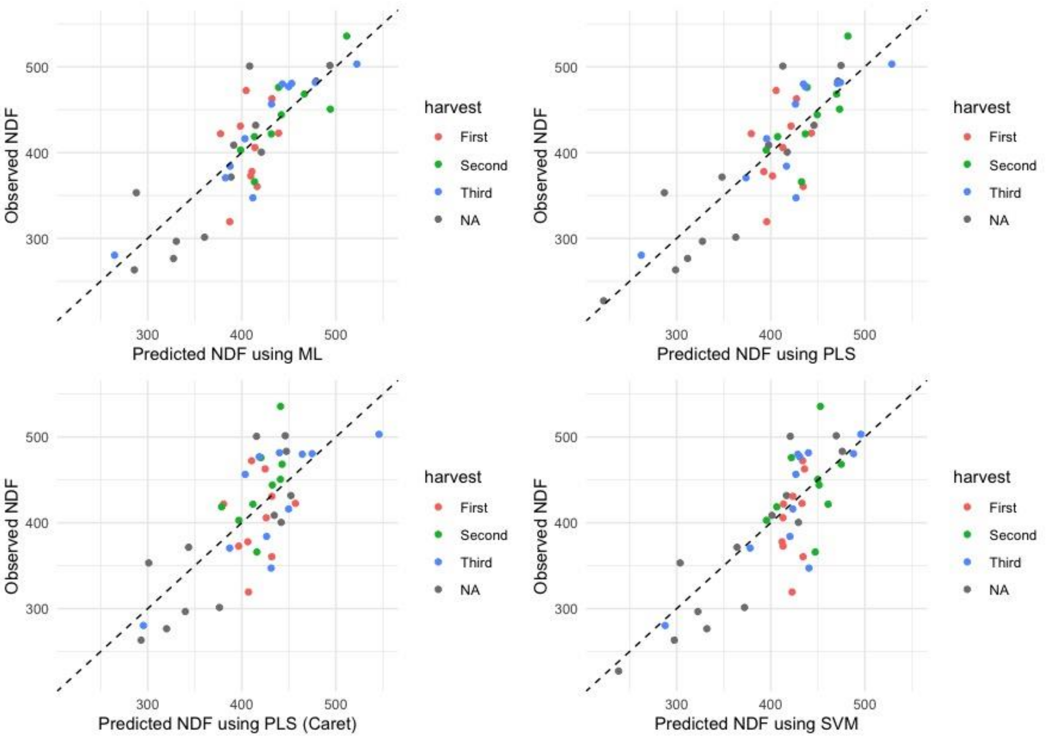

Figure 33. Predicted vs. observed neutral detergent fibre (NDF) (g/kg DM) for multiple linear regression (MLR), partial least squares (PLS), PLScaret, and support vector machine (SVM). Data

points are color-coded by site, red for first, green for second, blue for third, and grey for unkown (N/A).

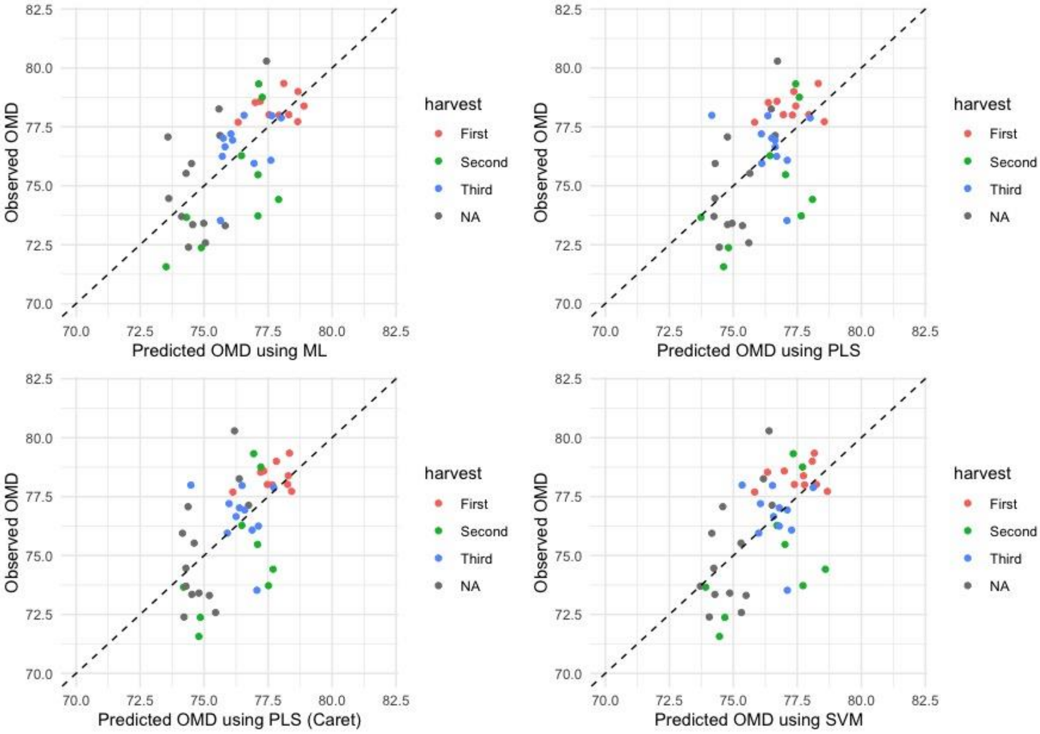

Figure 34. Predicted vs. observed organic matter digestibility (OMD) (%) for multiple linear regression (MLR), partial least squares (PLS), PLScaret, and support vector machine (SVM). Data points are color-coded by site, red for first, green for second, blue for third, and grey for unkown (N/A).

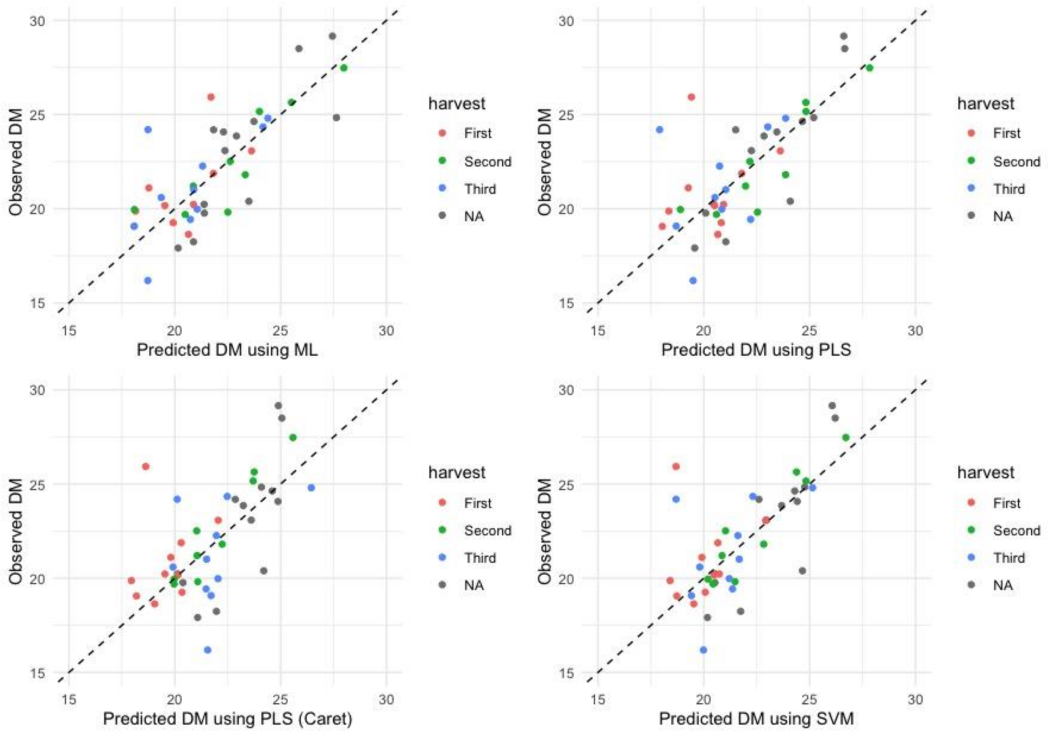

Figure 35. Predicted vs. observed dry matter (DM) (%) for multiple linear regression (MLR), partial least squares (PLS), PLScaret, and support vector machine (SVM). Data points are color-coded by site, red for first, green for second, blue for third, and grey for unkown (N/A).

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