Monitoring forage fields in Northern Sweden with satellite imagery (Vallsat)

Gradering av vallar I norra Sverige med hjälp av satellitbilder (Vallsat)

Image from Sentinel-2 satellite, acquired on the 2019-07-13. Data from European Space Agency.

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Summary

The aim of the Vallsat project was to evaluate the potential of Sentinel-2 satellites to monitor biomass and nutrition quality of leys in Northern Sweden. More than 540 samples were collected over 2 years from 4 sites of Northern Sweden. Several methods were tested to link the spectral information with the field data: vegetation index-based regression, multivariate regression based on the individual spectral bands of Sentinel-2, and a hybrid inversion of the PROSAIL radiative transfer model. Vegetation indices showed moderate performances for biomass prediction and poor performances for nutrition quality estimation (crude protein and neutral detergent fibre contents). The hybrid inversion approach of PROSAIL showed poor results for biomass prediction (it was not tested for nutrition quality estimation, as no parameter of the model could be used as a proxy for protein or neutral detergent fibre). Multivariate models, on the other hand, showed very promising performances, for both quantity and quality predictions. Indeed, the error of estimation was of 0.4 t/ha for dry matter yield and 17.0 and 26.1 g/kg DM for crude protein and neutral detergent fibre contents, respectively. More work is required to confirm these results, but the project confirmed the potential of the Sentinel-2 satellites to serve as a basis for a practical tool for farmers.

1. Introduction

Forage crops, predominantly mixed leys, are a cornerstone of the farming sector in Northern Sweden, where it represents more than 70% of the agricultural land use. Farmers aim to maximise harvest yield, while maintaining a high level of forage quality. Indeed, quantity and quality of produced forage have a direct influence on the economic and ecological performances of the meat and dairy production industries, as forages with low protein or energy concentrations require the use of concentrates to maintain the productivity, and low harvest yield needs to be compensated by purchasing extra feed. One of the main levers for maximising yield is N fertilisation, and N recommendations are based largely on expected biomass yield and clover content, which are both difficult to estimate. A tool for mapping the biomass and nutrition quality of a ley could assist the farmer with feed budgeting.

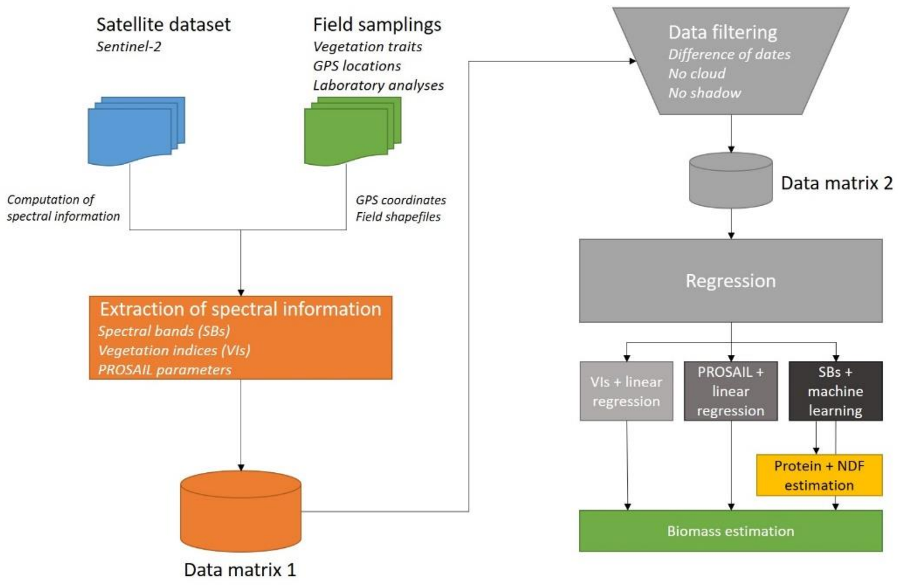

Figure 1. Summary of the workflow of the project.

Satellite remote sensing is largely used in agriculture to monitor the dynamics of crops based on their spectral signatures. The Sentinel-2 satellites provide open-access, ready for analyse images, at a spatial resolution that suits the operational needs for field monitoring in Northern Sweden. Moreover, these satellites have a high frequency of revisit (approximately 2 days at high latitudes). Last but not least, the sensor used on the Sentinel-2 satellites provides spectral information in 13 bands located in the visible, near infrared and shortwave infrared spectral regions. Although the visible and near infrared bands are commonly used to perform biomass estimation, very little work has been carried with the shortwave infrared bands to estimate the nutrition quality of the swards. Indeed, this region is used in the spectral-based laboratory methods to estimate the nutrition quality.

Therefore, the objective of the project is to evaluate how Sentinel-2 data could be used to monitor the biomass and quality of forage fields in Northern Sweden. The overall approach and workflow are summarised in Figure 1.

2. Material and methods

2.1. Field sampling

Data were collected over two years (2019 and 2020) at four sites located in Northern Sweden (Lännäs, Röbäcksdalen, Ås and Öjebyn). In total, height ley fields were used to harvest samples across the growing season to capture biomass and nutrition quality variability. For each measurement, three in-field locations were randomly selected, and for each of these locations, three samples were taken using 0.25m² sampling quadrats. For each of these samples, the following workflow applied: GPS coordinates were measured, the canopy height was measured using a ruler and the dominant grass and legume species were visually determined. At Röbäcksdalen only, two additional measurements were performed: (i) the leaf chlorophyll contents of 5 plants of grass and 5 plants of legume were measured to approximate the canopy chlorophyll content, and (ii) spectral readings were acquired from a Yara N-sensor. Samples were then harvested and taken back to the laboratory for manual separation of grass, legume and weeds species. Fresh samples were then dried for 48 hours at 60°C and further ground to pass a 1-mm sieve. In total, 549 samples were collected from the two years of the project. Samples acquired in 2019 (with the exception of the Öjebyn-acquired data, which were not estimated to be suitable for nutrition analysis) were sent for forage nutritional analysis by wet chemistry methods. Samples collected in 2020 were not sent for analysis, as the harsh winter conditions resulted in a high level of weeds in the harvested swards.

2.2. Satellite imagery

The Sentinel-2 constellation consists of two satellites that acquire images with 13 spectral bands from the visible, near infrared and shortwave infrared ranges, with a spatial resolution varying between 10-, 20- and 60-meters depending on the spectral band. Acquired images are managed by the European Space Agency and pre-processed for geometric and radiometric corrections, making them ready for analysis. All images are open-access and can be downloaded from the Copernicus hub[a]. A total of 275 Sentinel-2 images were downloaded over 2019 and 2020 for the four sites of the project.

2.2.1. Computation of vegetation indices

Vegetation indices (VIs) are a combination of two or more spectral bands. VIs are designed to maximize the effects of a vegetation-related trait, such as e.g. the aboveground biomass or the canopy chlorophyll content, while minimizing confounding effects such as e.g. soil reflected light or atmospheric aerosols. In total, 48 VIs were computed from the Sentinel-2 data (the complete list of VIs is provided in Appendix).

2.2.2. Performing inversion of the PROSAIL radiative transfer model

Radiative transfer models (RTMs) are physically-based models that describe the interaction of light with vegetation. The PROSAIL[1] RTM is a combination of the leaf PROSPECT model and of the canopy SAIL model. It describes reflected light patterns as a function of the chemistry of the leaf, of the structure of the canopy and of the geometry between the sun and the sensor. Using appropriate mathematical tools, RTMs can also be used to estimate vegetation traits such as leaf area index, leaf water content or leaf chlorophyll content from measured spectra. However, this type of operation requires a very rich spectral information, usually composed of hundreds of bands, which are not available from the Sentinel-2 data. Hybrid approaches are a combination of RTMs with machine learning algorithms, and have been proposed to overcome these limitations (e.g. Berger et.al[2]). The overall principle is to use RTM to generate a large theoretical spectra database, where each spectrum is linked to predefined values of the parameters of the RTM. These spectra will then be resampled to

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[a] https://scihub.copernicus.eu/

match Sentinel-2 spectral characteristics and used as explanatory variables in a machine learning algorithm, where the predefined chemistry and structure values of the canopy will be used as response variables. The prosail R package[3] was used to perform the hybrid inversion approach using support vector machine as the machine learning algorithm. The outputs consisted of estimated values of leaf area index and leaf mass per unit area, which are relevant proxies to estimate dry matter yield.

2.3. Regression modelling

Vegetation information was linked to the spectral information through two main approaches: (i) linear regression and (ii) multivariate regression. Linear regressions were used to link crop traits with either VIs computed from satellite images or PROSAIL-estimated canopy parameters. The *lm* function from the R stats package[5] was used to build the linear regression models. Multivariate regression models were used to link crop traits with the spectral bands from the Sentinel-2 images. Several algorithms were tested: partial least squares (pls R package[6]), random forest (randomForest R package[7]) and support vector machine (e1071 R package[8]). This choice was motivated by the fact that these different algorithms rely on various assumptions, and their outcomes might show significantly different performances.

Two metrics were used to evaluate the performances of the regression models, *i.e.* the coefficient of determination (R^2) and the root mean square error ($RMSE$).

3. Results and discussion

3.1. Biomass prediction

The results related to the biomass prediction were obtained by extracting the spectral information from the pixels of the satellite images that were related to the locations of the samples. The resulting database has been filtered to remove potential sources of error, like e.g. wrong measured spatial coordinates of the sampling locations, presence of clouds or shadows over the sampled area on the satellite image, etc. In total, 513 samples were available to build regression models.

3.1.1. Vegetation index-based regression

As expected, the different vegetation indices computed showed very contrasted performances (see example on Figure 2). The worst results were obtained for the Transformed Chlorophyll Absorption Reflectance Index (TCARI), with a $RMSE$ of 1.26 t/ha and a R^2 of 0.01. Saturation phenomena were observed for several VIs, like e.g. the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Red Edge Index (NDRE).

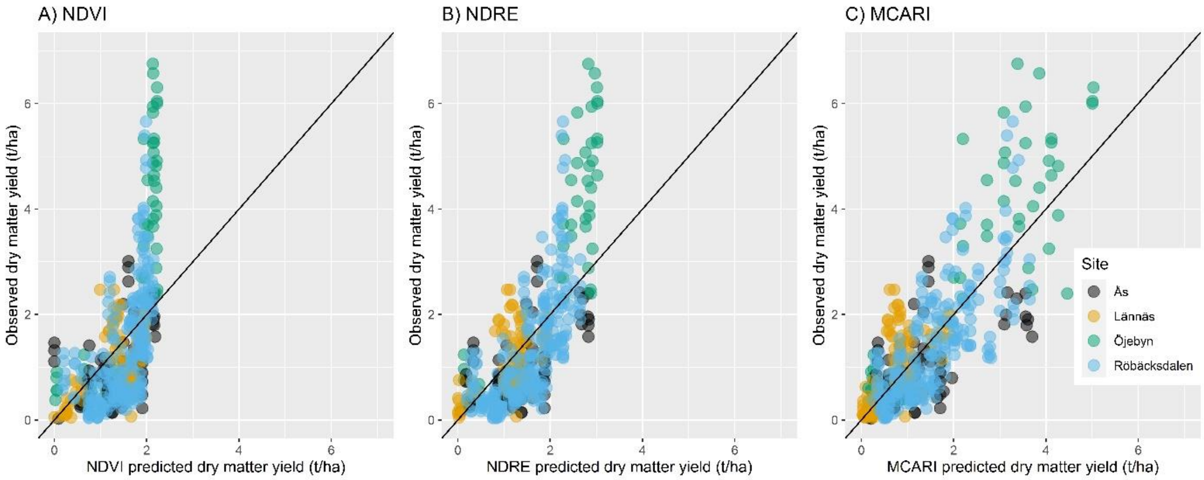

Figure 2. Observed vs Sentinel-2 predicted dry matter yield, expressed in tons per hectare. Three VIs (NDVI, NDRE, and MCARI) were selected among the 48 that were computed to show the range of performances.

This is illustrated on Figure 2 A and B, where predicted dry matter yields reach a threshold around 2 t/ha. The best performances were obtained for the Modified Chlorophyll Absorption in Reflectance Index (MCARI11, please refer to Appendix), with a $RMSE$ of 0.75 t/ha and a R^2 of 0.64 (Figure 2 C).

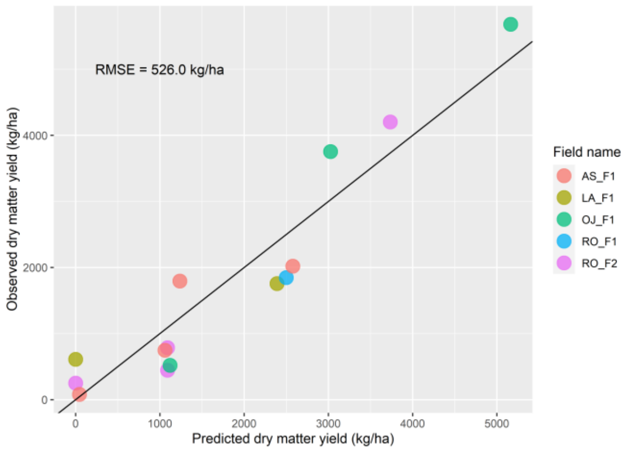

Figure 3. Dry matter yield prediction from time integrated values of NDVI. These results are preliminary and need to be further explored.

These results outline the limited potential of vegetation indices to monitor the dry matter yield for forage grassland. However, more approaches should be tested, and more particularly, the use of time series of vegetation indices. Such approach has been shown to overcome the saturation effect reported above, and preliminary results from the data acquired in the current project showed satisfactory performances (Figure 3). This will be further assessed in the coming year.

3.1.2. Multivariate regressions

Three multivariate regression models were tested for their capability to estimate the dry matter yield from the individual spectral bands of the Sentinel-2 images: partial least squares, random forest and support vector machine (hereinafter referred to as PLS, RF and SVM, respectively). Obtained results showed good performances, especially for the RF and SVM algorithms (Figure 4 and Table 1). With a validation $RMSE$ and R^2 of 0.4 t/ha and 0.91, respectively, RF appears to be a strong candidate for dry matter yield prediction from Sentinel-2 images.

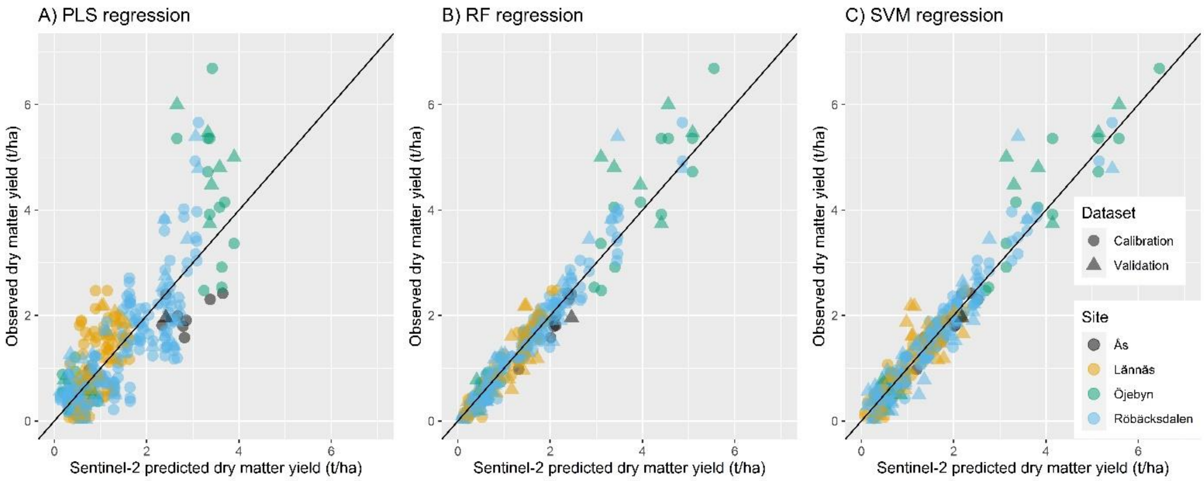

Figure 4. Observed vs predicted dry matter yields, expressed in tons per hectare. Predictions were performed with partial least squares (A), random forest (B) and support vector machine (C) regression algorithms.

However, it is important to emphasize that multivariate regression models in general, and machine learning algorithms in particular, are prawn to overfit: in other words, despite showing good performances with both calibration and validation datasets, there is no guarantee that these models will not fail if run on a new dataset. To overcome this limitation, the best option is to increase the size and the representativeness of the training dataset (e.g. collect new data from various regions in Sweden with contrasted climates, soil conditions, etc.)

Table 1. Statistics summary of the multivariate regression algorithms for the prediction of the dry matter yield.

Regression model	Dataset	$RMSE$ (t/ha)	R^2
PLS	Calibration	0.7	0.66
PLS	Validation	0.7	0.74
RF	Calibration	0.2	0.97
RF	Validation	0.4	0.91
SVM	Calibration	0.2	0.96
SVM	Validation	0.5	0.88

New datasets are currently being collected through the “Cybergrass 1” project, in collaboration with researchers from Finland. These datasets will be used to update the multivariate models presented here and evaluate their robustness.

3.1.3. PROSAIL hybrid inversion-based regression

Two parameters were obtained from the PROSAIL hybrid inversion approach that could be linked to biomass with a univariate linear regression approach: the leaf area index (LAI, expressed in m^2/m^2) and the leaf mass per area (LMA, expressed in g/cm^2). LAI is a common proxy for crop biomass estimation, as the accumulation of biomass is directly linked to the leaf area available for photosynthesis. The combination of LAI and LMA provides a direct estimation of the leaf dry matter yield, which is a close proxy for the whole plant dry matter yield, especially in the case of leys. However, the results obtained from this project showed poor performances, with R^2 smaller than 0.1 and $RMSE$ superior to 1.1 t/ha. Several hypotheses can be proposed to explain this: first, contrary to the VIs and multivariate regression approaches, and because of technical difficulties in the inversion process, the dataset used consisted of field averaged values of reflectance. This could partially explain the poor performances of the inversion approach, as fields showed clear patterns of heterogeneity, especially in 2020, due to the harsh winter conditions. Second, the inversion process heavily relies on the initial parameterization of PROSAIL, and the values used in this project might be suboptimal. This will be further assessed in the next year.

3.1.4. Biomass prediction: summary

Three approaches were tested to estimate the biomass of forage fields from Sentinel-2 images: VI-based univariate linear regression, individual spectral bands-based multivariate regression and PROSAIL inversion-based univariate regression. Among all these approaches, multivariate regressions showed the best performances, with random forest and support vector machine outperforming all other approaches. Although encouraging, caution is advised, as machine learning algorithms are prawn to overfit. Nevertheless, if confirmed, these results could be converted into a useful tool for farmers for biomass prediction. More work is also required for VI- and PROSAIL-based approaches before these methods can be discarded.

3.2. Nutrition quality prediction

Although samples were collected for quality analysis during the Vallsat project, the data used to build the following models were obtained from Hans Lindberg and Bengt-Ove Rustas in the framework of Vallprognos. The choice to not use the data collected from Vallsat was motivated by the fact that too few data were available. This is mostly due to the fact that data from 2020 were not suitable for analyses, due to their very high weeds contents, and that no data were available for Öjebyn in 2019 due to samples processing difficulties. In total, 87 samples collected in 2020 and 2021 from 28 farms located over all Sweden were used to build regression models for crude protein and neutral detergent fibre (NDF) prediction. Corresponding spectral information was extracted at the field level from Sentinel-2 images and further used for regression.

3.2.1. Vegetation index-based regression

Similar to biomass prediction, 48 VIs were computed from the Sentinel-2 images and further linked to crude protein and NDF using a univariate linear regression. All models showed poor performances, with most R^2 smaller than 0.05, both for crude protein and NDF predictions. The best performances were obtained with the normalized difference red edge index for the prediction of NDF, with a R^2 of 0.17, which remains too poor to be of any interest for a practical application. These results, however, need to be further controlled for potential issues before being discarded for good.

3.2.2. Machine learning-based regression

Partial least squares, random forest and support vector machine algorithms were tested on their capability to estimate the crude protein and neutral detergent fiber from Sentinel-2 individual bands.

Although all models showed satisfactory accuracy, RF outperformed both PLS and SVM (Figure 5, Figure 6 and Table 2).

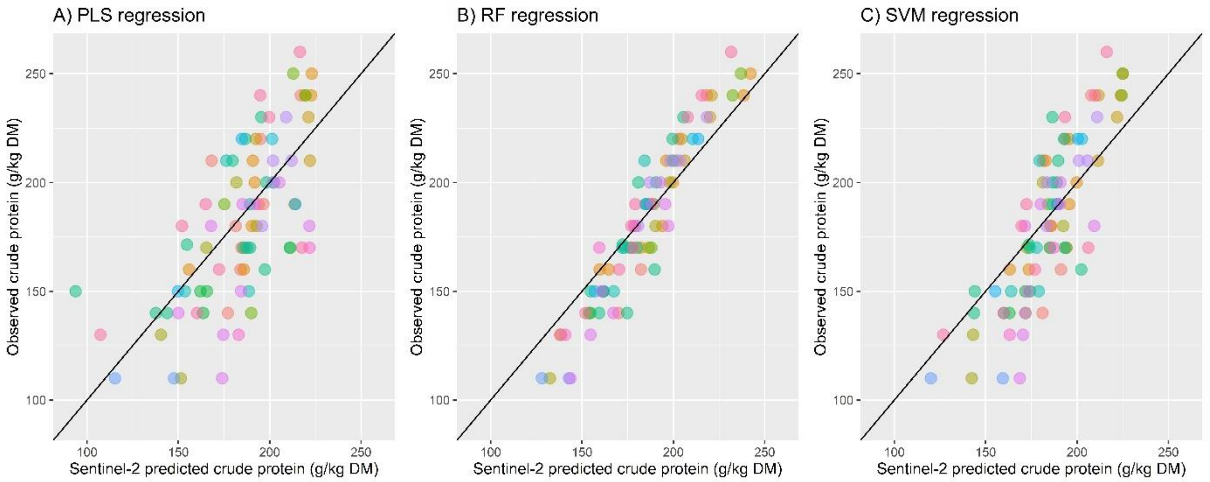

Figure 5. Observed vs predicted crude protein content, expressed in grams per kilograms of dry matter. Predictions were performed with partial least squares (A), random forest (B) and support vector machine (C) regression algorithms. The colour of the symbols codes for the sampling site.

With a $RMSE$ of 17.0 g/kg DM and a R^2 of 0.91, RF regression appeared to be the most accurate method to predict the crude protein concentration. The same conclusion applies for neutral detergent fibre content, with a $RMSE$ of 26.1 g/kg DM and a R^2 of 0.92.

Similar to what was mentioned for biomass prediction, it is important to consider these results with caution. In this case, no calibration/validation process was used due to the relatively small size of the dataset (n=87), and the performances might be overoptimistic. This will be further controlled with currently available and upcoming datasets.

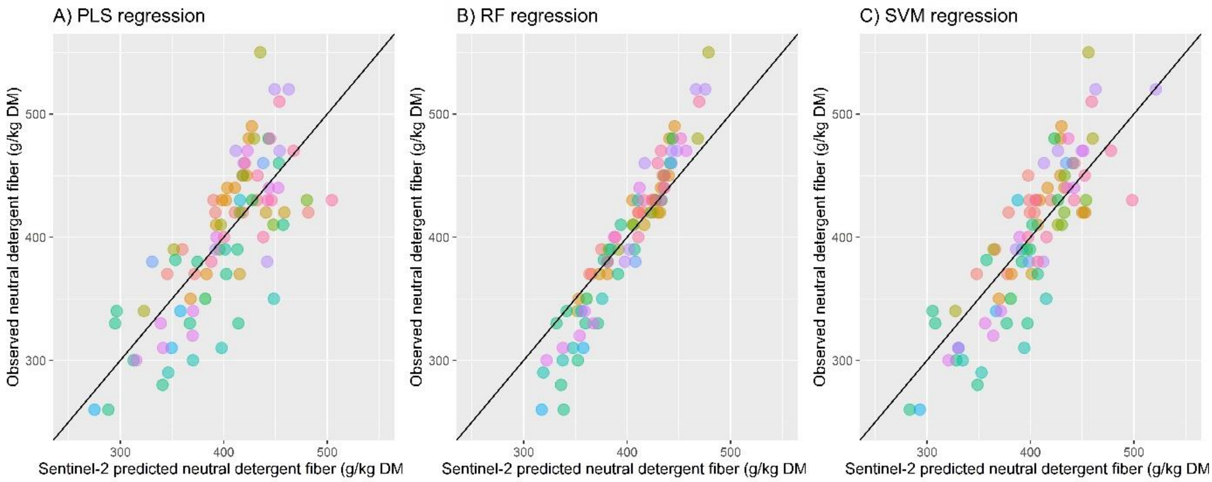

Figure 6. Observed vs predicted neutral detergent fiber content, expressed in grams per kilograms of dry matter. Predictions were performed with partial least squares (A), random forest (B) and support vector machine (C) regression algorithms. The colour of the symbols codes for the sampling site

Nevertheless, it is worth to note that the error percentage of RF algorithms for both crude protein and neutral detergent fibre fall below the 10% threshold (9% for crude protein and 6.5% for neutral detergent fibre). If their performances are confirmed, these models will be an asset for farmers to support management strategies.

Table 2. Statistics summary of the multivariate regression algorithms for the prediction of the crude protein and neutral detergent fiber contents.

Variable	Regression model	$RMSE$ (g/kg DM)	R^2
Crude protein	PLS	29.9	0.45
Crude protein	RF	17.0	0.91
Crude protein	SVM	25.5	0.68
NDF	PLS	40.2	0.58
NDF	RF	26.1	0.92
NDF	SVM	33.8	0.72

3.2.3. Nutrition quality prediction: summary

Vegetation index-based regression showed very poor performances for the prediction of both crude protein and neutral detergent fibre contents and are currently of no interest for monitoring the quality of forage grasslands. On the other hand, multivariate regression, especially random forest, showed very promising results, which however remain to be confirmed.

4. Summary of the results

4.1. Main outputs

- Multivariate regressions, especially machine learning algorithms (random forest and support vector machine) appear to outperform vegetation index- and PROSAIL inversion-based regression models, both for biomass and for quality predictions.
- More work is needed for the vegetation index- and PROSAIL inversion-based approaches for biomass prediction. The use of time series of vegetation indices could dramatically improve the performances of the prediction models, and a finer tuning of PROSAIL could also result in improved prediction performances.

4.2. Benefits for farmers

- The Vallsat project confirmed the potential of the Sentinel-2 data for dry matter yield prediction.
- These conclusions also apply for the prediction of crude protein and neutral detergent fibre contents.
- More work is being carried out to confirm current results, and new datasets are collected from other projects. This will allow to validate the potential of Sentinel-2 data for leys management support.
- If the performances of Sentinel-2 data-based models are validated, an updated version of CropSAT could be proposed to the farmers to get a free access to information that can support their management decisions.

4.3. Communication and collaborations

So far, no paper has been published from the current results. It is planned that the four following articles will be submitted to international scientific journals in the coming two years:

- Machine learning-based estimation of the biomass of forage swards from Sentinel-2 spectral data, Peng, J., Morel, J., Parsons, D., Söderström, M., Féret, J.-B. (draft)
- Sentinel-2 and Planet Dove NDVI time series to predict biomass production of forage grasslands (planned scientific paper)
- Multivariate regression on Sentinel-2 data to estimate nutrition quality of forage grasslands (planned scientific paper)
- PROSAIL hybrid inversion to estimate the biomass of forage grasslands (planned scientific paper)

A participation to the Joint XXIV International Grassland and XI International Rangeland Congress was planned, but did not happen due to the pandemic situation.

Data collection and analysis were supported by one Master student from SLU (Niklas Zeiner) and an undergraduate student from Toulouse University, France (Clémentine Bussière). More recently, a new postdoc has joined the NJV department (Junxiang Peng). His main work objective is to finalize the analyses of the Vallsat data and to help write scientific papers to valorise the results.

The results initiated in the Vallsat project will be continued through several collaborations: the nutrition quality data that will be acquired for Vallprognos in 2022 will be shared to improve the robustness of the models developed in Vallsat. International collaborations have been initiated: the Interreg project "Cybergrass 1" is currently being conducted with researchers from Finland, and a project has recently been submitted for funding by researchers in Norway where the experience and data acquired in Vallsat could be valorised and further developed.

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Appendix

Below is a list that includes names and formulas of every vegetation index calculated from Sentinel-2 images. Indices and references can be retrieved on indexdatabase.de

Name	Formula
CIRe1	$(nir - rededge1) - 1$
CIRe2	$(nir - rededge2) - 1$
CIRe3	$(nir - rededge3) - 1$
CVI	$(nir/green)/(red/green)$
DVI	$nir - red$
GCI	$(nir/green) - 1$
GDR	$green/red$
GDVI	$nir - green$
GMR	$green - red$
GNDVI	$(nir - green)/(nir + green)$
GOSAVI	$1.16 \times ((nir - green)/(nir + green + 0.16))$
GRVI	$nir/green$
IRECI1	$(nir - red)/(rededge2 - rededge1)$
IRECI2	$(rededge3 - red)/(rededge2 - rededge1)$
MCARI11	$((nir - rededge1) - 0.2 \times (nir - green)) \times (nir/rededge1)$
MCARI12	$((nir - rededge2) - 0.2 \times (nir - green)) \times (nir/rededge2)$
MCARI13	$((nir - rededge3) - 0.2 \times (nir - green)) \times (nir/rededge3)$
MCARI21	$((rededge1 - red) - 0.2 \times (rededge1 - green)) \times (rededge1/red)$
MCARI22	$((rededge2 - red) - 0.2 \times (rededge2 - green)) \times (rededge2/red)$
MCARI23	$((rededge3 - red) - 0.2 \times (rededge3 - green)) \times (rededge3/red)$
MTVI	$1.5 \times (1.2 \times (nir - green) - 2.5 \times (red - green))/\sqrt{(2 \times nir + 1)^2 - (6 \times nir - 5\sqrt{red} - 0.5)}$
NDI1	$(nir - rededge1)/(nir + red)$
NDI2	$(nir - rededge2)/(nir + red)$
NDI3	$(nir - rededge3)/(nir + red)$
NDRE1	$(nir - rededge1)/(nir + rededge1)$
NDRE2	$(nir - rededge2)/(nir + rededge2)$
NDRE3	$(nir - rededge3)/(nir + rededge3)$
NDVI	$(nir - red)/(nir + red)$
NNIR	$nir/(nir + red + green)$
OSAVI	$1.16 \times ((nir - red)/(nir + red + 0.16))$
REDVI1	$nir - rededge1$
REDVI2	$nir - rededge2$

REDVI3	$nir - rededge3$
RVI	nir/red
S2REP1	$705 + (35 \times (0.5 \times (nir + red) - rededge1)/(rededge2 - rededge1))$
S2REP2	$705 + (35 \times (0.5 \times (rededge3 + red) - rededge1)/(rededge2 - rededge1))$
SWIR_MCARI1	$((rededge1 - swir1) - 0.2 \times (rededge1 - green)) \times (rededge1/swir1)$
SWIR_MCARI2	$((rededge1 - swir2) - 0.2 \times (rededge1 - green)) \times (rededge1/swir2)$
SWIR_NRI1	$(swir1 - red)/(swir1 + red)$
SWIR_NRI2	$(swir2 - red)/(swir2 + red)$
SWIR_OSAVI1	$1.16 \times ((nir - swir1)/(nir + swir1 + 0.16))$
SWIR_OSAVI2	$1.16 \times ((nir - swir2)/(nir + swir2 + 0.16))$
SWIR_TCARI1	$3 \times ((rededge1 - swir1) - 0.2 \times (rededge1 - green) \times (rededge1/swir1))$
SWIR_TCARI2	$3 \times ((rededge1 - swir2) - 0.2 \times (rededge1 - green) \times (rededge1/swir2))$
TCARI1	$3 \times ((rededge1 - red) - 0.2 \times (rededge1 - green) \times (rededge1/red))$
TCARI2	$3 \times ((rededge2 - red) - 0.2 \times (rededge2 - green) \times (rededge2/red))$
TCARI3	$3 \times ((rededge3 - red) - 0.2 \times (rededge3 - green) \times (rededge3/red))$
TCI	$(rededge2 - rededge1)/(rededge1 - red)$