Evaluation of remote sensing vegetation indices to estimate forage yield and quality of different fertilized grassland

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Abstract

As many studies show, spectral signatures provide detailed information on plant functional traits. Forage yield and quality are of great importance in grassland management. Therefore, we derived widely used vegetation indices from hyperspectral reflectance data and evaluated their potential for estimating yield and quality on grassland plots with different fertilization. The spectral reflectance measurements were carried out shortly before each of three harvests per year with a field spectrometer on a long-term experiment with 24 organic and mineral fertilization treatments with a four-fold repetition. Starting with a null model, the best predictors for dry matter yield (DM, kg ha^{-1}) and crude protein content (CP, g kg^{-1}) estimation were determined from selected vegetation, chlorophyll and water indices and a leaf area index using an exhaustive search algorithm on a training data set. The estimation of DM with an index combination on an independent test data set yielded $R^2 = 0.76$, the CP was estimated with $R^2 = 0.69$. Additionally, we compared the index-based results with neural net analyses using Sentinel-2 bands calculated with spectral response functions (S2-SRF) as predictors. With a variety of observations, we have shown that simple indices can differentiate forage yield and quality on grasslands evolved under different levels of nutritional supply.

Keywords: spectral signatures, grassland yield, forage quality, Sentinel-2

Introduction

The great diversity of land use types and management intensities in grassland with very different plant communities is a big challenge for empirical and dynamic grassland models. As Reinermann *et al.* (2020) show in their overview, remote sensing with multi- and hyperspectral reflectance data offers a wide range of possibilities to get traits of plant stands, which represent the effects of site and management factors. Sensors on several platforms ranging from terrestrial systems like field spectrometers to UAVs and satellites are used for this purpose, supporting different spatial scales from field to global applications.

In this study, the potential of remote sensing vegetation indices was analysed by combining and verifying them for yield and quality estimates of highly diverse grasslands. These models were compared with an approach using the S2-SRF transformed Sentinel-2 bands (Klingler *et al.,* 2020) to show differences in using indices and original spectral information. Based on Sentinel-2 bands, models can be used in image-based applications on a large spatial scale.

Materials and methods

The evaluation of vegetation indices for estimating grassland yield and quality is based on hyperspectral data collected by the HandySpec Field VIS/NIR 1.7 (tec5) field spectrometer with a range from 400 to 1690 nm. The spectral measurements were taken on a long-term field fertilization experiment, established in 1946 in Admont (Styria, Austria) three times a year, immediately before each cut between 2015 and 2019.

The field experiment consists of 96 plots and shows a wide variability of well-established plant stands that have developed very differently over more than 70 years due to 24 continuous fertilization treatments, each repeated four times. Besides an unfertilized treatment, the other plots are supplied with mineral (N, P, K) and organic fertilizers (solid and liquid manure) in different combinations and levels.

From the obtained spectral signatures we calculated commonly used vegetation indices (NDVI, RVI, SAVI, EVI, RDVI, TVI, MTVI1 MTVI2, CARI, LCI, GI, PRI, REIP1, REIP2, LWVI1, LWVI2, NDNI, TGI (definitions see at indexdatabase.de)) and the Leaf Area Index (LAI). As described by Klingler *et al.*

(2020), we converted hyperspectral data into the corresponding Sentinel-2 bands using the S2-SRF (ESA, 2018) and we applied algorithms proposed by Baret *et al.* (2010) in combination with radiative transfer models for LAI calculation. We selected the indices with the highest prediction power for DM and CP using an exhaustive search algorithm on a training data set in R. Furthermore, we compared linear models (LM) based on the selected indices with an Averaged Neural Network (ANN) from the R package caret (Kuhn, 2008) were the S2-SRF bands B2, B3, B4, B5, B6, B7, B8, B8a, B11, and B12 were used as predictors. We split the data for both models in two different ways: i) a random split into 2/3 for training and 1/3 for the test, and ii) a split by years with 2015, 2016 and 2017 as a training set and 2018 and 2019 as a test set for the DM model and 2015 and 2016 as a training set and 2017 as a test set for the CP model (CP analyses were only available for three years). We optimized the model parameters using the R function "trainControl" for the training data set and evaluated the models by calculating R^2 and RMSE on the independent test data set.

Results and discussion

Among the calculated indices and all their combinations, the Leaf Water Vegetation Index 2 (LWVI2) (Galvão *et al*., 2005), a variant of the Normalised Difference Water Index (NDWI) in combination with the Normalised Difference Nitrogen Index (NDNI) (Serrano *et al*., 2002) provided the best estimation results for grassland yield. The best correlation between modelled and observed CP as a quality parameter was given in the combination of LWVI2 and LAI. Both results are shown in Figure 1.

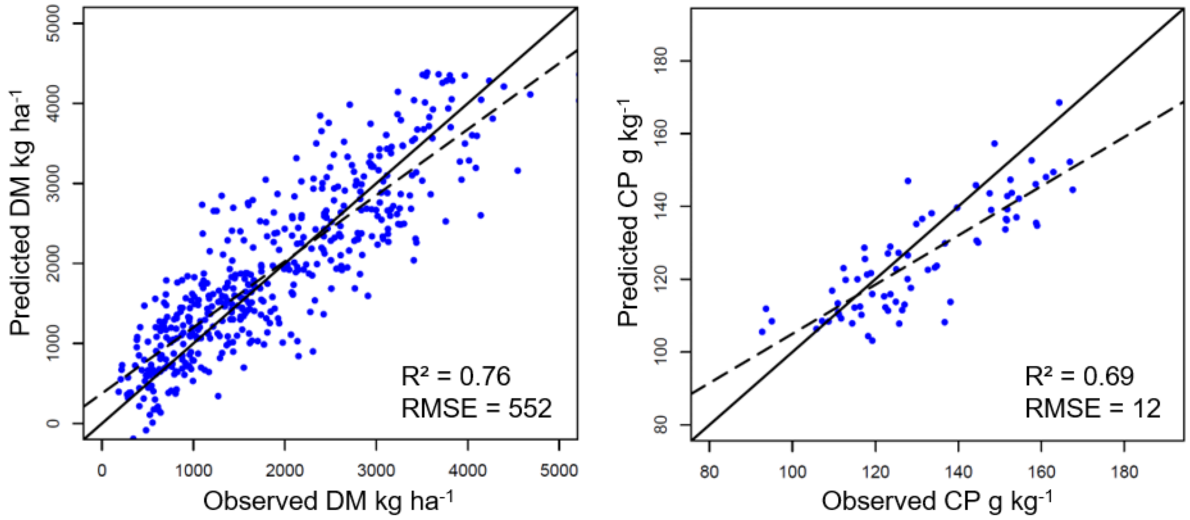

Figure 1. Estimation of DM and CP by a linear model using a random test dataset with LWVI2 & NDNI for DM and LWVI2 & LAI for CP.

The results of the ANN model with S2-SRF data are shown in Table 1 and can be compared there with the index-based results. The R^2 as well as the RMSE of both modelling approaches, are in a comparable range.

Table 1. Comparison of R^2 and RMSE results for randomly and yearly split test datasets, from a linear model (LM) with combination of two different indices and an Averaged Neural Network (ANN) using S2-SRF bands.

		Random split				Split by years			
		LM (2 Indices)		ANN (S2-SRF)		LM (2 Indices)		ANN (S2-SRF)	
	n	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE
Dry Matter kg ha^{-1}	1438	0.76*	552*	0.79	511	0.65	598	0.60	645
Crude Protein g kg^{-1}	360	0.69*	12*	0.74	10	0.71	13	0.72	11

* Results are plotted in Figure 1

By combining two indices, we are already using those parts of the electromagnetic spectrum that contribute most to the estimate. Therefore, extending the model to include all S2-SRF bands does not add much value. However, the direct use of Sentinel-2 bands supports a large-scale application.

To verify the model results, a data split is used in two ways. While a random split does not distinguish between replicates or survey years, a split by years applies the test to independent data from an entire year. This demonstrates the prediction power of each model for all three growths of an independent year.

Conclusions

The combination of remote sensing vegetation indices supports considerable estimates of yield and forage quality. We found that directly used multispectral data in neural networks achieve similar prediction accuracy as indices. For further development of the models, other predictors should be added, and the ground truth database needs to be extended to other sites and climate regions.

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