Suitability of non-destructive yield and quality measurements on permanent grassland

Klingler A.[1], Schaumberger A.[1], Vuolo F.[2] and Poetsch E.M.[1]

[1] *Institute of Plant Production and Cultural Landscape, Agricultural Research and Education centre Raumberg-Gumpenstein, Austria;* [2] *Institute of Geomatics, University of Natural Resources and Life Sciences, Vienna, Austria*

Abstract

There is an increasing interest in non-destructive measurements for comprehensive grassland monitoring. The present study aims to assess the ability of crop height (CH), leaf area index (LAI), chlorophyll content (CC) and mean developmental stage measurements to estimate dry matter yield (DMY), crude protein content (CP) and neutral detergent fibre content (NDF) of permanent grassland. Therefore, LAI from hyperspectral reflectance acquired by a field spectrometer and from the AccuPAR LP-80 was recorded weekly during an entire growing season. CH was measured with a rising plate meter (RPM) and a yardstick (YS) before destructive sampling for DMY, CP and NDF determination. The most abundant grass species were cut for measuring mean developmental stage and CC. Starting with a null model, the best predictors for DMY, CP and NDF using an exhaustive search were determined. Including design effects and the cuts in a mixed model approach, CH and LAI showed an R^2 of 0.93 for DMY estimation. CC from *Alopecurus pratensis* and CH were the best predictors for CP (R^2=0.86) and CC along with mean developmental stage from *A. pratensis* for NDF (R^2=0.81). The tested parameters and in particular parameter combinations led to promising results for DMY, CP and NDF estimation.

Keywords: grassland monitoring, leaf area index, crop height, yield, forage quality

Introduction

Grassland swards are well known for their high spatial and temporal variability due to abiotic and biotic influences during each growth (Schut *et al.*, 2002). To guarantee optimal and comprehensive grassland management during the entire growing period, information about yield and quality development are of utmost importance (Wachendorf *et al.*, 2018). Non-destructive methods for the estimation of yield and forage quality have become more common in recent years. These methods offer the possibility to monitor growth characteristics within particular cuts and thus optimise grassland management. Non-destructive observations mostly refer to the relationship of sward height, phenological stage, species composition or the interaction between leaves and radiation with yield and forage quality. In situ measurements provide valuable information at the local level, but are not very suitable for large scale observations due to their mostly labour-intensive execution (Ali *et al.*, 2016). In recent years, satellite data have proved to be very helpful for observing grasslands regionally. Especially the freely available Sentinel-2 data provide a sufficiently high temporal and spatial resolution (Drusch *et al.*, 2012). Few methods, and especially method combinations for the estimation of DMY, CP and NDF have been tested for species-rich permanent-grassland vegetation. This research aims to test common non-destructive measurements for their ability to predict the yield and quality of permanent grassland during an entire vegetation period.

Materials and methods

A field experiment was conducted in 2018 on permanent grassland in the Enns Valley, Austria (47°30'35.4' N; 14°05'03.5'E; 643 m above sea level). The experimental setup was established as a split-plot design with three replicates (2.25 m^2 per plot) before the start of the growing period in 2018. The sampling was carried out at weekly intervals during the entire vegetation period, which resulted in 32 campaigns, each following a precise workflow.

Initially, CH was measured using an RPM and a YS. Four hyperspectral reflectance measurements were acquired by a field spectrometer (HandySpec/tec5), and three AccuPAR readings were obtained at each plot. The hyperspectral reflectance data were resampled into Sentinel-2 bands according to the Spectral Response Functions (ESA, 2018). After resampling, LAI was calculated using a neural net algorithm from Baret *et al.* (2010). This algorithm is specifically tailored for Sentinel-2 data and was trained with radiative transfer simulations from the PROSPECT and SAIL models (Jacquemoud *et al.*, 2009; Verhoef, 1984). Following the non-destructive measurements, an area of one square meter was harvested on each plot. After drying the samples for DMY determination, CP and NDF were analysed chemically. Representing the abundance of the three most dominating species in the sward, fifteen individual plants of *Alopecurus pratensis,* ten of *Dactylis glomerata* and five of *Festuca pratensis* were manually cut on the remaining edges of the harvested plots for the following analyses. CC measurements were carried out using a chlorophyll meter (SPAD 502) and were then separated into observations on the flag leaf and observations on randomly selected leaves. Subsequently, the mean developmental stage of each grass species according to the BBCH-scale (Meier *et al.*, 2009) was calculated by the following two equations:

$$MSC = \sum_{i=1} \frac{S_i * N_i}{C}$$

where MSC = mean stage count, S_i = growth stage index, N_i = number of plants in stage S_i and C = total number of plants in the sample population (Moore *et al.*, 1991).

$$MSW = \sum_{i=1} \frac{S_i * D_i}{W}$$

where MSW = mean stage weight, S_i = growth stage index, D_i = weight of plants in stage S_i and W = total weight of plants in the forage sample (Fick and Mueller, 1989). The best and the two best predictor variables were determined using exhaustive search from the function 'regsubsets' of the 'leaps' R-package. The response variables were DMY, CP and NDF. Explanatory variables included in the models were: crop height (RPM and YS), LAI from AccuPAR and field spectrometer, CC from *A. pratensis*, *D. glomerata* and *F. pratensis* (flag leaves and random leaves of each species), MSC and MSW of *A. pratensis*, *D. glomerata* and *F. pratensis* and average MSC and MSW of all three species. After defining the best explanatory variables, a mixed model regression was set up using the function 'lmer' of the 'lme4' R-package. The dataset was split into 67% training data and 33% test data for the calculation of *RMSE* and R^2.

Results and discussion

CH (RPM) was identified by the exhaustive search method to be the best predictor for DMY. It showed an R^2 of 0.90 and an *RMSE* of 434 when testing the mixed model regression on the test data set. The two best response variables for DMY estimation were CH (RPM) and LAI from AccuPAR. The predictor combination led to an improved *RMSE* (Figure 1). The combination of CH (RPM) and LAI from field spectrometer showed a high prediction accuracy as well (R^2=0.92, *RMSE*=363), indicating the high potential of remote sensing data for grassland yield estimation. CH (YS) was the best predictor for CP (R^2=0.75, *RMSE*=22). The combination of the two best predictors, CH (YS) and CC from *A. pratensis* (random leaves) improved the prediction accuracy again (Figure 1). MSC from *F. pratensis* served as the best predictor for NDF (R^2=0.55, *RMSE*=50) whereas MSW from *A. pratensis* and CC from *A. pratensis* (random leaves) were the best predictors for NDF. The parameter combination again improved the prediction accuracy (R^2=0.81, *RMSE*=42). The prediction accuracy increased in all three cases (DMY, CP and NDF) when two explanatory variables were included in the model. This shows that the combination of morphological, phenological and optically sensed parameters significantly improves the model performance. LAI, CC, CH, mean developmental stage and in particular, their combination prove their ability for the prediction of yield and forage quality.

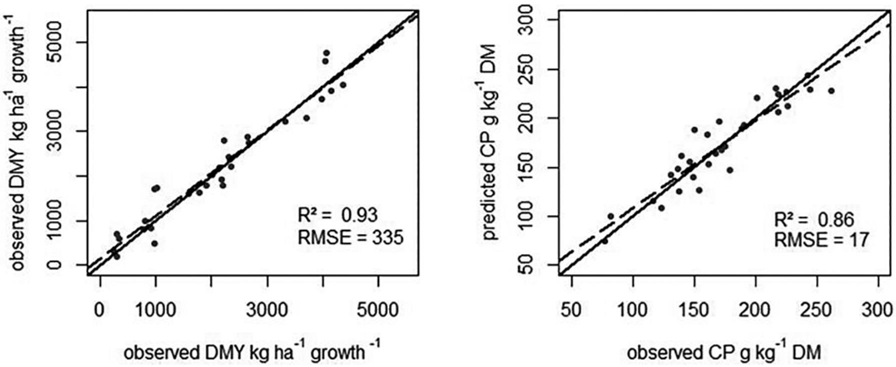

Figure 1. Observed vs predicted dry matter yield (DMY) kg ha^{-1} using rising plate meter (RPM) and leaf area index (LAI) from AccuPAR (left) and observed vs predicted crude protein (CP) g kg^{-1} dry matter (DM) using crop height and chlorophyll content (CC) from *Alopecurus pratensis* (random leaves) on the right side.

Conclusions

Non-destructive measurements on high abundant plants, as well as on the total sward, and a combination of both, show a high ability to estimate cost-efficiently and expeditiously some important yield and quality parameters of species-rich permanent grassland. The results demonstrate the possibility of continuous and comprehensive growth monitoring from small plots to regional scale. The planned extension of the experiment to several sites will provide reliable and robust results for a larger range of grasslands.

References

Ali I., Cawkwell F., Dwyer E., Barrett B. and Green S. (2016) Satellite remote sensing of grasslands: from observation to management. *Journal of Plant Ecology* 9, 649-671.

Baret F., Weiss M., Bicheron P. and Berthelot B. (2010) Sentinel-2 MSI products WP1152 algorithm theoretical basis document for product group B. INRA-EMMAH, Avignon, France.

Drusch M. *et al.* (2012) Sentinel-2: ESA's optical high-resolution mission for GMES operational services. *Remote Sensing of Environment* 120, 25-36.

ESA (2018) Sentinel-2 spectral response functions. Available at: https://earth.esa.int/web/sentinel/user-guides/sentinel-2-msi/document-library/-/asset_publisher/Wk0TKajiISaR/content/sentinel-2a-spectral-responses.

Fick G.W. and Mueller S.C. (1989) Alfalfa: quality, maturity, and mean stage of development. *Information Bulletin Cornell University* 217, 16.

Jacquemoud S. *et al.* (2009) PROSPECT + SAIL models: a review of use for vegetation characterization. *Remote Sensing of Environment* 113, 56-66.

Meier U. *et al.* (2009) The BBCH system to coding the phenological growth stages of plants – history and publications. *Journal für Kulturpflanzen* 61, 41-52.

Moore K.J., Moser L.E., Vogel K.P., Waller S.S., Johnson B.E. and Pedersen J.F. (1991) Describing and quantifying growth stages of perennial forage grasses. *Agronomy Journal* 83, 1073-1077.

Schut A.G.T., Ketelaars J.J.M.H., Meuleman J., Kornet J.G. and Lokhorst C. (2002) AE – automation and emerging technologies: novel imaging spectroscopy for grass sward characterization. *Biosystems Engineering* 82, 131-141.

Verhoef W. (1984) Light scattering by leaf layers with application to canopy reflectance modeling: the SAIL model. *Remote Sensing of Environment* 16, 125-141.

Wachendorf M., Fricke T. and Möckel T. (2018) Remote sensing as a tool to assess botanical composition, structure, quantity and quality of temperate grasslands. *Grass and Forage Science* 73, 1-14.