Proximal sensing techniques to monitor pasture quality and quantity on dairy farms

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Abstract

Regular and timely measurements of pasture quality and quantity allow dairy farmers to make effective decisions ensuring an adequate supply of nutrients to animals, efficient utilization of pasture, manipulation of stocking rates, management grazing intervals, and optimisation of input resources (e.g. nitrogen fertilisers) which results in more economic, environmentally aware, sustainable grazing systems.

The objectives of this research were to investigate the potential of proximal sensing tools to estimate pasture quality parameters (crude protein, CP; acid detergent fibre, ADF; neutral detergent fibre, NDF; ash, dietary cation-anion difference, DCAD; lignin, lipid, metabolisable energy, ME and organic matter digestibility, OMD) in mixed pastures. Three proximal sensors, ASD FieldSpec® Pro FR spectroradiometer (hyperspectral), Cropscan™ (multispectral) and Crop Circle™ (multispectral), were employed in this study.

In the hyperspectral study, the spectral reflectance measurements of pasture samples were acquired using an ASD FieldSpec® Pro FR spectroradiometer which has a spectral range of 350-2500 nm and attached with canopy pasture probe (CAPP) to ensure ambient light conditions. The acquired spectral data were pre-processed by various procedures: spectral averaging, smoothing and derivative transformation, then partial least squares regression was applied to regress against the corresponding measured values. The regression model was validated with an external dataset to evaluate the reliability and robustness of the model. The performance of both calibration and validation models were more or less similar. The validation model predicted the pasture quality parameters CP, ADF, NDF, ash, DCAD, lignin, ME and OMD with reasonable accuracy ($0.65 \leq R^2 \leq 0.83$; $1.70 \leq RPD \leq 2.48$; $0.64 \leq NSE \leq 0.83$) and the lipid was predicted with lower accuracy (R^2-0.55; RPD-1.44; NSE-0.50).

Cropscan relies on sunlight for its energy source and measures reflectance in 16 broad wavebands; it was evaluated for its potential to assess pasture quality parameters that are collected in one season. The relationship between spectral reflectance measured using the Cropscan and pasture quality parameters were established using single wavebands, new vegetation indices and stepwise multiple linear regression (SMLR) and the models were validated with an external dataset. Of all the models, the new non-linear new combination of RDVI index models were performed satisfactory results ($0.65 \leq R^2 \leq 0.85$) for predicting CP, DCAD, ME and OMD. CP, ash, DCAD, lipid, ME and OMD were estimated with moderate accuracy ($0.60 \leq R^2 \leq 0.80$) using the SMLR model. The Cropscan instrument was also used to test the potential for predicting pasture quality in different seasons (autumn, spring and summer). Improved accuracy was observed with season-specific models as compared to the combined season dataset models.

A three channel active optical sensor, Crop Circle™ was used to estimate herbage biomass and standing crude protein (SCP) using various indices. The results showed that the three channel based pasture index proved a reliable index for estimating biomass ($R^2 = 0.69$; RMSE = 518 kg ha^{-1}) and SCP ($R^2 = 0.77$; RMSE = 110 kg ha^{-1}) with moderate accuracy. Based on the calibration of PI, spatial analysis was assessed for biomass in ten dairy fields. In spatial analysis, semivariograms revealed the spatial dependency for biomass was moderate to strong and varied between the fields.

This study indicates that proximal sensors have considerable potential for real-time *in situ* assessment of pasture quality and quantity in mixed pastures. The results indicate that spectral resolution and number of wavelengths used in the sensor are crucial for determining pasture quality with high accuracy which would allow future research to develop proximal sensors with an optimal number of wavelengths and spectral resolution.

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Acronyms

AI	artificial intelligence
ANN	artificial neural networks
AOAC	association of official analytical chemists
ASD	analytical spectral devices – ASD Inc.
ADF	acid detergent fibre
AVIRIS	airborne visible infrared imaging spectrometer
CAPP	canopy pasture probe
CCRS	canada centre for remote sensing
CV	coefficient of variation
DCAD	dietary cation-anion difference
DM	dry matter
EM	electromagnetic
FDR	first derivative reflectance
FOV	field of view
GIS	geographic information system
GPS	global positioning system
IR	infrared
LAI	leaf area index
LIBERTY	leaf incorporating biochemistry exhibiting reflectance and transmittance yields
LV	latent variable
ME	metabolisable energy
MIR	mid infrared
NASA	national aeronautics and space administration
NDF	neutral detergent fibre
NDVI	normalised difference vegetation index
NIR	near infrared region
NSE	nash-sutcliffe efficiency
NV	nutritive value

NIRS	near infrared reflectance spectroscopy
OMD	organic matter digestibility
PCA	principal component analysis
PCR	principle component regression
PLSR	partial least squares regression
PRESS	predicted residual error sum of square
R^2	coefficient of determination
RDVI	renormalized difference vegetation index
REP	red edge position
RMSE	root mean square error
RMSECV	root mean square error of cross-validation
RMSEP	root mean square error of prediction
RPD	ratio prediction to deviation
SD	standard deviation
SAIL	scattering by arbitrarily inclined leaves
SAR	synthetic aperture radar
SAVI	soil adjusted vegetation index
SMLR	stepwise multiple linear regression
SWIR	shortwave infrared
SVM	support vector machines
SVR	support vector regression
USDA	united states department of agriculture
UV	ultra violet
VI	vegetation indices
VIP	variable importance for the projection
Vis/VIS	visible
Vis-NIRS	visible near infrared spectroscopy