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J.G.P.W. Clevers, G.W.A.M. van der Heijden, S. Verzakov, and M.E. Schaepman

Abstract
In this paper, the potential of a band shaving algorithm based on support vector machines (SVM) applied to hyperspectral data for estimating biomass within grasslands is studied. Field spectrometer data and biomass measurements were collected from a homogeneously managed grassland field. The SVM band shaving technique was compared with a partial least squares (PLS) and a stepwise forward selection analysis. Using their results, a range of vegetation indices was used as predictors for grassland biomass. Results from the band shaving showed that one band in the near-infrared region from 859 to 1,006 nm and one in the red-edge region from 668 to 776 nm used in the weighted difference vegetation index (WDVI) had the best predictive power, explaining from 66 to 77 percent of grassland biomass variation. Indices based on short-wave infrared bands performed worse. Results could subsequently be applied to larger spatial extents using high-resolution airborne digital cameras (for example, Vexcel’s UltraCam™).

Introduction
For efficient grassland management, information on the grassland status and its spatial variation within fields is of the utmost importance. Farmers need such information at early growth stages for guiding the fertilizer supply within fields in order to achieve optimal growth. Towards the end of the growing phase, such information is required for an early yield prediction and determination of the optimal time of harvest. Currently management is mainly based on qualitative expert knowledge. Quantitative information on the actual status of grass swards at the right moment in the season is preferred. Traditionally, destructive field measurements have been very tedious, time-consuming and not applicable to large areas. However, they have been used extensively to calibrate local, statistical-based models. In order to map the spatial variability of vegetation variables over large areas, airborne or spaceborne instruments are more suitable. A major constraint for applying remote sensing techniques is that the variability of the biophysical and chemical variables of grass swards on farmer’s fields in practice may be quite limited. Much remote sensing research has been performed on experimental fields with a large variability in biophysics of the canopy. In this study, we will focus on spectral information that can be used to predict spatial patterns even when the grass inherent variation of structure and biochemistry is limited.

Both statistical and physical approaches have been used for describing the relationship between spectral measurements and biophysical variables of vegetation. Statistical methods are based on regression models using either the original spectral bands or transformations on the spectral bands as independent variables. For the latter, a whole range of vegetation indices has been developed for estimating variables like biomass and leaf area index for a range of vegetation types (Broge and Leblanc, 2001; Daugtry et al., 2000; Haboudane et al., 2004; Haboudane et al., 2002; Schlerf et al., 2005; Thenkabail et al., 2002). Traditionally, most vegetation indices have been broadband indices based on red and near-infrared (NIR) bands. For estimating leaf chlorophyll and nitrogen concentration narrow spectral bands (of 10 nm width or less) have shown to be important, for instance for deriving information on the red-edge position (Broge and Leblanc, 2001; Clevers and Jongschap, 2001). Physical-based methods often use radiative transfer models describing the interaction of radiation with the plant canopy based on physical principles. Subsequently, model inversion is used for estimating biophysical properties of the canopy (Atzberger, 2004; Combal et al., 2003; Jacquemoud et al., 2000).

One problem that arises when using hyperspectral data as explanatory variables is the high dimensionality: they require many observations to achieve a good description of the distribution in high dimensional space (the so-called curse of dimensionality). Thus, the variance-covariance matrix is generally poorly estimated, and this can lead to worse prediction results compared to using less explanatory variables. Besides, hyperspectral data often show a high degree of collinearity of neighboring bands. This collinearity decreases the intrinsic dimensionality of the dataset, which would mean that fewer observations are required. However, nearly linearly-related variables make the variance-covariance matrix nearly singular. This leads to problems with matrix inversion and yields highly unstable parameter estimates. Generally, feature reduction (e.g., principal components transformation and partial least squares) or feature selection (e.g., stepwise linear regression) techniques are applied to...
overcome these problems (Bruzzone and Serpico, 2000).
The advantage of feature selection is that the derived features are
easily interpretable from a physical point of view. This is
not the case for, e.g., the principal components obtained
from hyperspectral data. When feature selection techniques
reduce the dimensionality of hyperspectral data, they should
preserve the key information content within a few spectral
bands.

A recent development in the field of feature selection are
methods known as shaving (Verzakov et al., 2004). Shaving
methods for spectroscopic data first detect correlation
between spectral bands, and based on these correlations, the
feature selection is performed. Final features are averages of
continuous bands of wavelengths. As stated before, such features
are easily interpretable from a physical point of view
(Verzakov et al., 2004). In this paper, we apply a modification
of a shaving algorithm based on support vector machines
(svm). Subsequently, the features (possibly narrow or broad
spectral bands) can be implemented in a simple regression
model.

The objective of the present study is to compare differ-
ent spectral-based approaches for predicting biomass of
grassland. The main goal is the derivation of the optimal
spectral bands based on an svm-modified, band shaving
algorithm. Results will be compared with partial least
squares and stepwise regression techniques. The latter
techniques do not use the fact that neighboring wavelengths
are highly correlated, thus neglecting this useful a priori
information. In addition to regression models using the
optimal spectral bands, various vegetation indices, which
make use of the previous results, will be tested. The various
phases of the study include:

- To assess the overall potential of hyperspectral data in
  a predictive model using partial least squares (plS) techniques,
- To select the optimal narrow-band spectral bands by a
  stepwise linear regression technique,
- To define the optimal spectral bands by a svm band shaving
  technique. This may not only result in narrow-band features,
  but also in broad-band features, and
- To test the potential of vegetation indices as predictors for
  grassland biomass.

Data Description

Field Data

At the “Droevendaal” experimental farm in Wageningen (the
Netherlands), a total of 20 plots were defined within a 2.2 ha
grass field with a mixture of grass species and white clover.
These plots were each 15 m long and 3 m wide with a
spacing of approximately 10 m between the plots. Plots
were harvested using a plot-harvester on 30 July 2004.
The biomass was recorded with a built-in weighing unit on
the harvester. After cutting, drill samples were taken from
the harvested material. These samples were oven dried during
72 hours at 70°C. After drying, samples were weighed again
for determination of dry matter weight.

Table 1 summarizes the destructive measurements
performed for the 20 plots of the grass/clover experiment.
Yield figures were at a high level for all plots. The plots
were defined within a normally treated grassland field and
no treatment differences existed between the various plots.
As a result the range in yield figures is not widespread,
which may limit the predictive power of spectral measure-
ments highly correlated, i.e., the model was fitted with noisy
observation i, and then observation i was predicted using this
model. This was performed for all observations (n) iterati-
vely. The number of latent variables selected was chosen
as parsimonious as possible, by taking the minimal number

<table>
<thead>
<tr>
<th></th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>RMSE</th>
<th>CV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Biomass (t/ha)</td>
<td>10.91</td>
<td>24.39</td>
<td>17.79</td>
<td>3.30</td>
<td>0.19</td>
</tr>
<tr>
<td>DM weight (kg/ha)</td>
<td>2186</td>
<td>4187</td>
<td>3346</td>
<td>487</td>
<td>0.15</td>
</tr>
<tr>
<td>DM content (%)</td>
<td>16.24</td>
<td>21.33</td>
<td>18.96</td>
<td>1.08</td>
<td>0.06</td>
</tr>
</tbody>
</table>

Field Spectrometer Data

On 29 July 2004, a field campaign with an ASD FieldSpec®
Pro FR spectroradiometer (www.asdi.com) was performed.
The FieldSpec® Pro spectroradiometer was deployed using a
fiber optic cable with a 25° field of view. Measurement
height above the plot was about 1 to 1.5 m. As a result, the
field of view at the plot level was circular with a radius
ranging from 0.22 to 0.33 m. About 10 measurements per
plot were performed, whereby each measurement represents
the average of 50 readings at the same spot. The sampling
interval was 1 nm. Although weather conditions were
constant with a very low atmospheric turbidity; the spectro-
radiometer was calibrated regularly using a Spectralon white
reference panel. Noisy regions were left out from further
analysis. These were the spectral regions below 450 nm,
above 2,400 nm, and water absorption bands at 1,350 to
1,450 nm and 1,800 to 1,950 nm.

Methods

Partial Least Squares

Regression models with hyperspectral data as explanatory
variables are often based on partial least squares (plS)
techniques (Hansen and Schjoerring, 2003; Huang et al.,
2004; Kooistra et al., 2004). PLS techniques are capable of
dealing with high dimensional input data with a high degree
of collinearity. They apply regression modeling between the
observed spectral data and the response variable to select a
limited number of latent variables. PLS techniques are simple
to use, fast, and they show a relatively good performance
(Thissen et al., 2004). Like with principle components, the
physical interpretation of the latent variables is difficult.

In a first step, all ground spectroradiometer measure-
ments (the explanatory variables) were used to estimate the
response variables (fresh biomass and dry matter weight)
using PLS models. In order to obtain an unbiased estimate of
the prediction error, a nested leave-one-out (LOO) analysis
was applied. The nested approach was used to select the
optimal number of latent variables at the inner loop, while
still having an unbiased prediction error at the outer loop.
To select the number of latent variables in the PLS-model,
the root-mean-square error of cross-validation (RMSECV)
was calculated as:

$$\text{RMSECV} = \sqrt{\frac{\sum (\hat{y}_i - y_i)^2}{n}},$$  (1)

where $\hat{y}_i$ and $y_i$ were the leave-one-out predictions and
observed values of the variable of interest (the response
variable), i.e., the model was fitted with noisy observation
$i$, and then observation $i$ was predicted using this
model. This was performed for all observations ($n$) iterati-
vely. The number of latent variables selected was chosen
as parsimonious as possible, by taking the minimal number

Table 1. Summary Statistics for the 20 Plots of the Grass/Clover Experiment (Harvested on 30 July 2004). (RMSE = Root Mean Square Error; CV = Coefficient of Variation)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>RMSE</th>
<th>CV</th>
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</tr>
</tbody>
</table>
of latent variables whose root-mean-square error of cross validation (RMSECV) was not significantly different from the overall minimum RMSECV, using a randomisation t-test ($\alpha = 0.10$) (Van der Voet, 1994).

To obtain insight in the prediction capability of the model, we use the percentage of variation accounted for by the cross validated model (using the leave-one-out predictions) with regard to the total variation in the dataset:

$$Q^2 = 1 - \frac{\sum_i (\hat{y}_i - y_i)^2}{\sum_i (y_i - \bar{y})^2},$$  \hspace{2cm} (2)

where $\bar{y}$ is the average value of the response variable of interest. Note that the predicted $\hat{y}$ is not used in the training and selection of the PLS model. By using an iterative approach, a prediction for every observation is obtained. The $Q^2$ has strong resemblance with the traditional coefficient of determination $R^2$ but can become negative if the prediction of the model is inadequate (e.g., in case of overfitting). For calculating $R^2$ $\hat{y}_i$ in Equation 2 is calculated from one regression equation using all observations instead of using the leave-one-out predictions. The $Q^2$ is (as $R^2$) strongly sensitive to the variation within the data set, so it should be considered with caution.

**Stepwise Forward Selection**

Reducing the dimensionality of hyperspectral imaging by selecting just a few contiguous regions may produce affordable and robust multispectral systems for airborne and spaceborne applications. A simple feature selection technique often used in hyperspectral remote sensing is the stepwise linear regression (Serrano et al., 2002). With this technique the optimum set of (individual) spectral bands for estimating vegetation variables is selected. As a model becomes more complex (more variables), it is able to adapt to more complicated underlying structures in the data set, but the prediction error increases. In general, there is an optimal model complexity that gives minimum expected prediction error (Hastie et al., 2001).

A stepwise forward selection approach was applied on all wavelengths of the FieldSpec® data. The number of predictors was limited to three variables, including the intercept, because of the small sample size of the experiment. The $Q^2$ was calculated using a leave-one-out procedure: select best set of bands on $n-1$ plots and use last one for the prediction error, and repeat this for all plots.

**SVM Band Shaving**

Then, the support vector machine band shaving algorithm as proposed by Verzakov et al. (2004) was used to select the best spectral bands as predictors in this experiment. The SVM band shaving algorithm is based on the SVM recursive feature elimination (SVM RFE) approach for a classification problem (Guyon et al., 2002). The idea of this approach (SVM RFE) is similar to the so-called backward feature selection. SVM RFE starts from the complete set of features and eliminates them one by one in such a way that the classification performance of the classifier, trained on the remaining features, is the best for this particular number of features. SVM RFE also starts from the complete set of features, which results in a set of feature weights $w_i, i = 1 \ldots p$. The feature with the smallest absolute value $|w_i|$ is considered to be the least important and is removed from the feature set. This procedure continues until the desired number of features or classification performance is reached. To speed up computations one can remove some predefined portion of features with the lowest absolute weights. In theory it is possible to use any other linear classifier. But at the first step, we have to deal with high-dimensional data, and it is desirable if not necessary to employ robust classifiers (like SVM) which do not suffer from overtraining.

In Verzakov et al. (2004) SVM band shaving was proposed, which is an adaptation of the SVM RFE for spectroscopic data. SVM band shaving, like SVM RFE, starts from the training of the linear SVM classifier on the complete feature set. Then, the obtained set of feature weights $w_i$ is considered as a (discrete) function with a natural ordering of the argument $i$ (as in the case for wavelength in spectroscopic data). The local minima of this function are expected to be boundaries between highly correlated spectral regions responsible for different sources of variation relevant for the discrimination problem. (Note, that the last statement is not a theoretical result but a heuristic definition supported by empirical studies. More discussion on this topic will be published elsewhere.) All the features situated between two neighboring minima are considered as belonging to one band and averaged out (with taking into account the sign of the corresponding $w_i$) to form a new feature. Of course, the problem of finding local minima for a discrete function is ill-posed, and one needs to use smoothing to compute derivatives. After extraction of the new features (bands), the standard SVM RFE is applied to this new feature set. Such a modification of the algorithm uses a priori knowledge about spectroscopic data: spectral values at neighboring wavelengths are highly correlated. It helps to prevent tedious work on elimination of many very similar features. And, what is more important, it automatically combines features from contiguous regions in single bands.

In this paper, we deal with regression not with a classification problem. So, SVM band shaving had to be adapted to a regression context for this purpose. Hence, we employed linear SVM regression (Vapnik, 1998) instead of linear SVM classification.

**Vegetation Indices**

Vegetation indices are often used as predictors for vegetation variables in a statistical way. The exact specification of an index depends on the available spectral bands at hand. For instance, the same indices can be applied to both narrow and broad spectral bands, yielding different values for the same index on the same object. Many studies have been performed comparing the information content using narrow spectral bands from hyperspectral imagery with the information content based on traditional broad spectral bands (Schlerf et al., 2005; Thenkabail et al., 2002). The estimation of biophysical vegetation properties shows an improved sensitivity when using narrow spectral bands (Elvidge and Chen, 1995; Gong et al., 2003; Hansen and Schjoerring, 2003).

The use of vegetation indices is the most common way to drastically reduce the dimensionality of the data set. The advantage is that also non-linear functions can be used for defining vegetation indices. A cross-section of frequently used vegetation indices (VIs) was tested in this research. This included the traditional Normalized Difference Vegetation Index (NDVI) and Simple Ratio (SR) index (Rouse et al., 1974), the soil-correcting indices like the Soil-Adjusted Vegetation Index (SAVI) (Huete, 1988) and the Weighted Difference Vegetation Index (WDSVI) (Clevers, 1989), the atmosphere-correcting Global Environmental Monitoring Index (GEMI) (Pinty and Verstraete, 1992), red-edge (RE) indices like the Guyot method (Guyot and Baret, 1988), Lagrangian interpolation (Dawson and Curran, 1998) and the...
second derivative (Demetriadesshah et al., 1990), the Enhanced Vegetation Index (EVI) as used for MODIS data (Huete et al., 2002), and the MERIS Terrestrial Chlorophyll Index (MTCI) as used for MERIS data (Dash and Curran, 2004). Recently, a lot of attention is also being focused on using the short-wave infrared (SWIR) region of the electromagnetic spectrum because SWIR wavelengths penetrate better into the canopy than red wavelengths. This way, saturation problems of some of the traditional vegetation indices using red and NIR wavelengths are reduced. The SWIR wavelengths are related to canopy water content that has a close correlation with canopy biomass and leaf area index (Hunt, 1991). Most relevant canopy water related indices are the Water Index (WI) (Penuelas et al., 1997) and the Normalized Difference Water Index (NDWI) (Gao, 1996). Although the original NDWI used wavelengths at 860 nm and 1240 nm, the version using 1,640 nm and 2,130 nm instead of the 1,240 nm are also being used (Chen et al., 2005). Indices were calculated for the 1 nm spectral bands. Subsequently, if possible, they were also calculated for the spectral bands obtained from the SVM band shaving. Again the leave-one-out procedure was applied for determining the predictive power of the vegetation indices.

Results and Discussion
The small variation of the vegetation characteristics within the grass/clover experiment studied is confirmed by the harvesting statistics in Table 1. In particular the dry matter content shows a low variability across plots. As a result we expect similar results when we try to estimate either fresh biomass or dry matter (DM) weight in this study. Figure 1 confirms that the dry matter weight and the fresh biomass are highly correlated.

Figure 2 shows the mean, minimum, and maximum of the spectral signatures for the 20 grassland plots. This figure shows that also the spectral variation between the plots is rather small. Variation is most pronounced in the NIR part of the electromagnetic spectrum. However, the NIR region also exhibits highest reflectance values. When looking at the coefficient of variation (CV), by dividing the root-mean-square error per wavelength by the corresponding mean spectral reflectance, we see that this CV is in the range of 0.04 to about 0.08 for the whole spectrum (Figure 3), when omitting the well-known atmospheric water absorption features. This figure also shows that the second water absorption feature should be extended to about 1,960 nm in order to avoid noisy measurements.

The relationship between canopy reflectance measurements as measured with the FieldSpec® spectroradiometer and biophysical (biomass) vegetation parameters are studied by plotting the correlation coefficients (correlograms) (Figure 4). The patterns of correlation were similar for fresh biomass and dry matter weight across all wavelengths. Spectral bands in the visible part of the spectrum up to about 715 nm exhibited a negative correlation with fresh biomass and dry matter weight. In the NIR and SWIR regions, spectral bands showed a positive correlation with these characteristics. In general, the best correlations were obtained between spectral measurements and fresh biomass. The best correlation coefficient was found at 937 nm for fresh biomass and dry matter yield. In addition to the 937 nm spectral band, the 1,135 nm spectral band also showed a relatively high correlation with fresh biomass and dry matter yield (Figure 4). Both 937 nm and 1,135 nm are situated just at the lower wavelength shoulder of water absorption features situated at about 970 nm and 1,200 nm (Curran, 1989). Both wavelengths are highly correlated ($R^2 = 0.96$) for this data set. Because of the strong correlation between fresh biomass and dry matter weight, we will mainly focus on the prediction of fresh biomass further on in this study.

Partial Least Squares
Results of the prediction of the fresh biomass using all narrow-band spectral measurements obtained with the
spectroradiometer and using a PLS model are shown in Table 2. Based on a randomization t-test only one latent variable had to be used for the PLS model. The PLS model accounted for 55 percent of the variation ($Q^2$) within the fresh biomass.

**Stepwise Forward Selection**

Stepwise forward regression applied to the FieldSpec® measurements yielded two spectral bands as optimum result for the fresh biomass. Table 2 provides the results of the stepwise linear regression. Results indicate that, in addition to the 937 nm wavelength band already observed in Figure 4, the red-edge region also provided significant information. For fresh biomass (and also for dry matter weight), this was at the 724 nm band. Noticeable, the latter spectral region on its own does not show a high correlation with these vegetation variables. However, in combination with the 937 nm spectral band it is significant. Other studies also showed the significance of wavelengths at the red-edge region in addition to the NIR region in estimating vegetation biophysical properties (Hansen and Schjoerring, 2003; Schlerf et al., 2005; Thenkabail et al., 2000). Results show a smaller $Q^2$-value than the $Q^2$-value obtained with the PLS models, indicating that some information is lost by selecting just these two bands in a simple linear model.

**SVM Band Shaving**

Subsequently, SVM band shaving was applied as another feature reduction technique. Figure 5 shows the effect of an increasing number of features in terms of $Q^2$-value for fresh biomass. From this figure we can conclude that the predictive power of a model with three up to 19 features has a $Q^2$ above 0.6, which can be considered as good for this dataset.

For fresh biomass, the three main features were the following wavelength ranges: (a) 668 to 776 nm, (b) 777 to 858 nm, and (c) 859 to 1,006 nm. We see that 724 nm from Table 2 is within the first interval and 937 nm is within the third interval. The same three features as found for fresh biomass were also found as main features for dry matter weight. Table 2 summarizes the observed results. The explained variation in fresh biomass using the three broad bands obtained from shaving is better than the one obtained for one latent variable with PLS. It is noticeable that again the red-edge region is found as a very important feature.

**Vegetation Indices**

Finally, the range of vegetation indices mentioned before was tested as predictors for fresh biomass. For most traditional indices like SR, NDVI, WDI, SAVI, GEMI, and EVI, wavelengths of 670 nm and 870 nm were used for the red and NIR bands, respectively. For the EVI also the band at 450 nm in the blue was used. Best result was obtained for the classic SR; whereas results for the NDVI, the MTCI (hyperspectral index) and the NDWI were nearly the same as for the SR.

## Table 2. Results of the Biomass Prediction in Terms of $Q^2$ and RMSECV Using PLS (a), Stepwise Forward Selection (b) and SVM Band Shaving (c)

<table>
<thead>
<tr>
<th>Vegetation Index</th>
<th>Wavelengths Used</th>
<th>$Q^2$-value</th>
<th>RMSECV</th>
</tr>
</thead>
<tbody>
<tr>
<td>SR</td>
<td>670/870</td>
<td>0.47</td>
<td>2.40</td>
</tr>
<tr>
<td>NDVI</td>
<td>670/870</td>
<td>0.44</td>
<td>2.47</td>
</tr>
<tr>
<td>WDI</td>
<td>670/870</td>
<td>0.20</td>
<td>2.95</td>
</tr>
<tr>
<td>SAVI</td>
<td>670/870</td>
<td>0.22</td>
<td>2.92</td>
</tr>
<tr>
<td>GEMI</td>
<td>670/870</td>
<td>0.18</td>
<td>2.98</td>
</tr>
<tr>
<td>EVI</td>
<td>450/670/870</td>
<td>0.23</td>
<td>2.90</td>
</tr>
<tr>
<td>MTCI</td>
<td>681/709/754</td>
<td>0.45</td>
<td>2.44</td>
</tr>
<tr>
<td>RE – Guyot method</td>
<td>670/700/740/780</td>
<td>0.38</td>
<td>2.61</td>
</tr>
<tr>
<td>RE – Lagrangian</td>
<td>700 to 740 interval</td>
<td>0.12</td>
<td>3.10</td>
</tr>
<tr>
<td>WI</td>
<td>900/970</td>
<td>0.33</td>
<td>2.70</td>
</tr>
<tr>
<td>NDWI</td>
<td>860/1240</td>
<td>0.43</td>
<td>2.49</td>
</tr>
<tr>
<td>NDWI-1640</td>
<td>860/1640</td>
<td>0.37</td>
<td>2.62</td>
</tr>
<tr>
<td>NDWI-2130</td>
<td>860/2130</td>
<td>0.22</td>
<td>2.91</td>
</tr>
</tbody>
</table>
derivative and the Lagrangian technique), were not the best predictors for the fresh biomass. Actually these were developed for predicting chlorophyll content of the leaves. Also the indices using wavelengths in the SWIR region were not better than the traditional indices using red and NIR wavelengths.

Results could be improved in this study by using the wavelength at 937 nm instead of the one at 870 nm. Of course, this does not apply to the red-edge related indices or to the SWIR related indices. Table 4 now provides the results. Again the SR and NDVI show the best results. The predictive power of the SR and NDVI clearly increased and the $Q^2$-values are rather high when comparing them with the results of the PLS, the stepwise regression and the band shaving. This may be due to the non-linearity of these indices. Figure 6 illustrates the relationship between the measured fresh biomass and the predicted fresh biomass using the SR.

Another option would be to use the best spectral bands from the band shaving analysis for calculating the vegetation indices. The first and third band obtained covered the two bands obtained with the stepwise linear regression for fresh biomass and dry matter yield. Therefore, we decided to use the 668 to 776 nm band obtained from the band shaving as red band in the SR, NDVI, WDMI, SAVI, and GEMI calculations. The 859 to 1,006 nm band was used as NIR band. The WDVI (Clevers, 1989) appeared to be the best predictor for fresh biomass (Table 5). With these broad spectral bands, it was not possible to derive specific red-edge indices or indices including the SWIR region. Also the EVI could not be calculated since a band in the blue wavelength region was not selected in the shaving. With these two broad bands results were worse than when using the best narrow bands, but still results illustrate the potential of this approach. Results using the first and second band of the band shaving result for fresh biomass yielded slightly worse results.

Conclusions

In this study, we investigated the optimal spectral bands derived from ASD FieldSpec® spectroradiometer measurements for predicting grassland biomass. Subsequently, the optimal spectral bands were used in a range of vegetation indices as predictors. The potential of a new band shaving technique based on support vector machines (SVM) was tested and compared with a conventional stepwise linear regression and partial least squares (PLS) technique. Results indicate that PLS provides in general a good prediction power. However, it does require the recording of all wavelengths. Stepwise forward regression yielded a narrow band at 937 nm and one at 724 nm as best predictors. Limiting the number of bands to only three broad bands using SVM band shaving yielded good results, which were even slightly better than without band selection. The results indicate that in addition to one band in the NIR region (either 777 to 858 nm or 859 to 1,006 nm) a spectral band in the red-edge region (668 to 776 nm) is important for predicting fresh and dry biomass when using a vegetation index. The broad bands do include the narrow-band results obtained from the stepwise regression. Best result was obtained for the WDVI, but we should note that we tested a lot of vegetation indices and selected the most suitable one from the dataset. This results tentatively in an over-estimation of the prediction power. This is not the case for the (nested) leave-one-out approach applied in PLS and stepwise regression.

Perspectives

Frequent measurements of grass canopy relevant variables during the growing season are a major prerequisite for predicting quality and yield. Future research will focus on the deployment of such technologies allowing for robust estimates with a limited number of spectral bands. Various approaches seem to be feasible having sufficient predictive modeling potential, however little converging of approaches in choosing and proposing appropriate band combinations is seen. This paper proposes to use an advanced algorithm called SVM band shaving to converge to common band sets more quickly.
for the potential need to shift spectral band selection under varying phenological phases or background signals. The best spectral bands obtained by the SVM band shaving now would be serious options in a simple multispectral system for predicting the fresh biomass of grasslands. An imaging system (either airborne or spaceborne) could then be used for mapping purposes. For illustrating the potential of such a system, we applied the previous findings to airborne UltraCam™ digital images available for this experiment.

Vexcel’s UltraCam™ digital camera system delivers large format aerial imagery that is radiometrically and geometrically superior to images captured by conventional film cameras at a comparable price (Schiwee, 2005). The UltraCam™ system comprises a panchromatic band and four multispectral bands. On 28 July 2004 the grassland field was recorded using the UltraCam™ digital camera by Aerodata International Surveys. The flight altitude was about 2,790 m, resulting in a pixel size of 0.25 m for the panchromatic band (450 to 665 nm) and 0.78 m for the multispectral bands (blue: 420 to 475 nm, green: 455 to 580 nm, red: 635 to 675 nm, and NIR: 700 to 805 nm). Aerodata performed a geometric correction for the internal camera geometry and a radiometric correction for vignetting and white balance. The pixel values of the UltraCam™ images were converted to surface reflectance by using reference targets, measured in the same campaign with the FieldSpec® spectroradiometer. Spectral sensitivity curves as provided by Vexcel Corporation were used for calculating the target reflectance for the UltraCam™ spectral bands. An empirical line transformation was used in order to correct for camera calibration and atmospheric effects (Clevers et al., 2005). Average reflectance values per plot were based on about 45 pixels within the plot boundaries.

The spectral bands do not really match the bands obtained from the band shaving method, although the red and NIR band of the UltraCam™ do show correspondence with the first two bands obtained as best from the band shaving. Therefore, the red and NIR bands of the UltraCam™ were also used for calculating the broad-band indices used in this study and the same prediction procedure of fresh biomass was applied as before. Results are given in Table 6. The WDI obtained the best predictive power for these bands. Results are worse than in case of the more optimal bands found before. A linear regression model was then applied to the WDI obtained from the UltraCam™ images for the entire field, thus providing a prediction map of the fresh biomass. The result is shown in Figure 7. We may improve measurements of field heterogeneity of biophysical variables with remote sensing devices like the UltraCam™ camera by using more appropriate bands (filters) using band-selection procedures as we have applied in this paper.

Acknowledgments

We would like to thank Fred Hagman from Aerodata International Surveys for providing the UltraCam™ data and Vexcel Corporation for providing the specifications and spectral sensitivities of the UltraCam™ camera.

Table 6. Results of the Best Vegetation Indices Using the Red and NIR Spectral Bands of the UltraCam™ Digital Camera System

<table>
<thead>
<tr>
<th>Vegetation Index</th>
<th>Wavelengths used (nm)</th>
<th>$Q^2$-value</th>
<th>RMSECV</th>
</tr>
</thead>
<tbody>
<tr>
<td>NR</td>
<td>635 to 675/700 to 805</td>
<td>0.35</td>
<td>2.67</td>
</tr>
<tr>
<td>NDI</td>
<td>635 to 675/700 to 805</td>
<td>0.38</td>
<td>2.61</td>
</tr>
<tr>
<td>WDI</td>
<td>635 to 675/700 to 805</td>
<td>0.40</td>
<td>2.54</td>
</tr>
<tr>
<td>SAVI</td>
<td>635 to 675/700 to 805</td>
<td>0.39</td>
<td>2.58</td>
</tr>
<tr>
<td>GEMI</td>
<td>635 to 675/700 to 805</td>
<td>0.34</td>
<td>2.69</td>
</tr>
</tbody>
</table>

Figure 7. Spatial pattern of the estimated biomass (t/ha) for the grass-clover parcel at the “Droevendaal” experimental farm, Wageningen, based on the spectral information of an UltraCam™ image. The biomass was estimated from the wdi, obtained from the UltraCam™ image, using the following equation: Biomass (t/ha) = $-16.9 + 0.619 *$ WDI/$(%)$. A color version of this figure is available at the ASPRS website: www.asprs.org.

References


