LAI ASSESSING OF WHEAT STANDS FROM AISA-DUAL IMAGERY

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ABSTRACT:

In this study the spatial assessment of the LAI for a wheat field in Saxony-Anhalt (Germany) from hyperspectral imagery (AISA-DUAL) is presented. Prediction of LAI has been carried out by partial least squares regression (PLSR) with the PARLeS software using in-situ LAI measurements and their corresponding spectra in the hyperspectral imagery. The LAI was predicted with values of r^2_{cv} higher than 0.85. In order to assess the influence of the number of spectral bands on LAI prediction, AISA-DUAL spectra have been resampled by spectral binning to 50% (183 spectral bands) and 33% (122 spectral bands) of the original number of spectral bands, respectively. Predicted LAI obtained from hyperspectral imagery were well in line with in-situ LAI measurements and represented the spatial inner-field variations.

1. INTRODUCTION

Biochemical properties like chlorophyll content, water content and mineral components influence the spectral reflectance of plants. In this context the leaf area index (LAI) allows to draw conclusions on the photosynthetic activity (Duchemin et al., 2006) and hence the productivity of vegetation which makes it a state variable of crop growth models. The LAI is an important factor for high quality of yield estimates in agriculture since it is strongly influenced by yield reducing factors such as plant diseases and mismanagement (Boegh et al., 2002; Carter, 1994; Daughtry et al., 1992). In the past the spatial assessment of seasonal dynamics of the LAI was limited by in-situ measurement techniques. While during past decades LAI prediction from optical remote sensing data was mainly performed by utilizing multispectral sensors, hyperspectral data has already proven the potential for higher quality of LAI prediction (Lee et al., 2004, Jarmer 2013). Furthermore, the availability of several new hyperspectral sensors permits to assess the seasonal LAI dynamics with high spatial accuracy. In this study the spatial assessment of the LAI for a wheat field in Saxony-Anhalt (Germany) from hyperspectral imagery provided by the AISA-DUAL system will be presented.

2. STUDY AREA AND DATA

2.1 Study area

The study site (11°54′E, 51°47′N) is located close to the city of Köthen, Saxony-Anhalt, Germany (fig. 1). This region is characterized by a slightly undulated tertiary plain with an altitude of 70 m above sea level which is covered by a thin Loess layer. Since the study site is located in the rain shadow of the Harz Mountains, the region is distinctly dry with 430 mm mean annual precipitation. The investigated field has a size of approx. 80 ha cropped with winter wheat (*Triticum aestivum*). Chernozems in conjunction with Cambisols and Luvisols form the predominant soil type. Soils properties are highly diverse with fine-scale patterns of soil texture and organic matter.

2.2 Field data

Field survey was performed after a spring drought period and during dry weather conditions on 7th and 8th May 2011. In total, 37 sampling plots (50 × 50 cm²) of winter wheat at stem elongation have been measured under clear sky conditions and the exact position of each sampling plot has been located by differential GPS (fig. 1). Green leaves area index (LAI) was determined using a SunScan (Delta-T Devices Ltd., USA) using the average of six measurement at each sampling plot. To exclude non-representative single measurements, the average was calculated for measurements which were within one standard deviation.

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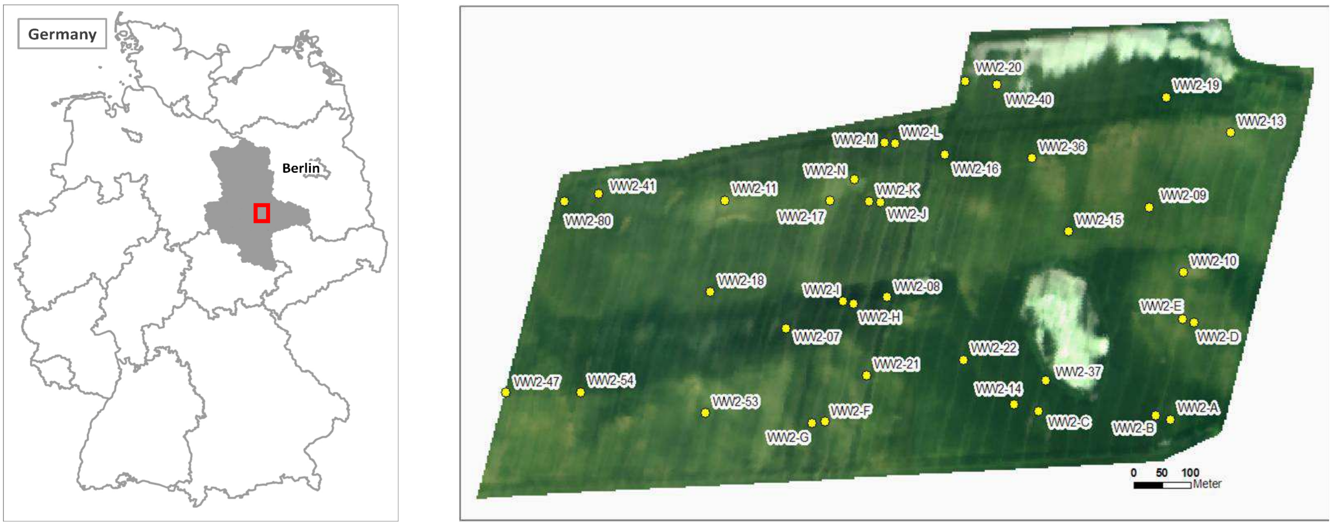

Figure 1. Location of the test site with the investigated field in the federal state of Saxony-Anhalt in Germany (left) and investigated wheat field with sampling plots positions (background AISA-DUAL) (right)

2.3 Hyperspectral imagery

Hyperspectral data of the airborne system AISA-DUAL (Specim Ltd.) was used for the spatial mapping of the LAI. AISA-DUAL is a hyperspectral pushbroom scanner combining the AISA-EAGLE (VIS/NIR, 400-1000 nm) and the AISA-HAWK (SWIR, 1000-2500 nm) sensor. The AISA-DUAL imagery of the study site was acquired on 10^{th} of May 2011 in 367 spectral bands in the wavelength range of 400-2500 nm with a spatial resolution of 3 m. During pre-processing of the image data the ROME destriping algorithm (Rogaß et al., 2011) was applied to reduce sensor miscalibration effects leaving deficient lines along track in the images. FLAASH (Fast Line-of-sight Atmospheric Analysis of spectral Hyper cubes) was used for atmospheric correction and an empirical line correction was conducted with spectral ground measurements of different dark and bright targets collected in the test site during AISA-DUAL data acquisition time (Smith and Milton, 1999). The geometric correction of the AISA-DUAL data was realized with the software CaliGeo while orthorectification was performed with the software ENVI. In total, three imagery stripes were combined to allow analysis of the entire wheat field.

3. METHODS

For noise reduction and in order to assess the influence of the number of spectral bands on LAI prediction, AISA-DUAL spectra have been resampled by spectral binning. Spectral binning is a commonly used method to reduce noise in hyperspectral data. In this context adjacent spectral bands will be summed up to one new single binned spectral band to enhance the signal-to-noise ratio (SNR) of the data (Dell'Endice et al., 2009). In this study spectral binning was performed averaging two and three adjacent original spectral bands of the AISA-DUAL data to generate one new spectral band, respectively. In this way the number of spectral bands was reduced from 367 to 183 and to 122, respectively and the SNR could be improved. Furthermore, spectral bands in the range of the water vapour absorption bands (1354-1411 nm, 1807-1996 nm) and selected bands at the beginning and at the end of the AISA-DUAL spectral range (400-418 nm, 2410-2500 nm) were deleted due to strong noise in this spectral region of the AISA-DUAL system leaving 100, 150 and 300 spectral bands for further analysis. Thereafter, the spectral signatures of the image pixels corresponding to the geographic position of the different wheat samples were extracted from the three AISA-DUAL data sets.
Prediction of LAI has been carried out by partial least squares regression (PLSR) with the PARLeS software (Viscarra Rossel, 2008) using the in-situ LAI measurements and their corresponding spectra in the hyperspectral imagery. The maximum of latent variables (rank) used in the PLS was limited to ten. The optimum number of latent variables used for the regression was determined by comparing the $RMSE_{cv}$ of predictions obtained from models with different numbers of latent variables. PLSR model results were cross-validated (cv) according to the 'leave-one-out-method', which means that each sample was estimated by an empirical-statistical model that was calibrated using the remaining (n-1) samples (Otto, 2007). The coefficient of determination (r^2_{cv}) and the root mean squared error ($RMSE_{cv}$) were calculated to assess the prediction accuracy. In addition, the ratio of prediction to standard deviation (RPD) was determined by dividing the standard deviation of the measured values by the $RMSE_{cv}$ (Malley et al., 2004).

4. RESULTS AND DISCUSSION

Due to the early seasonal time the LAI value of the sampling plots measured in the field was relatively low varying in a range between 0.50 m^2 m^{-2} at minimum and 3.40 m^2 m^{-2} at maximum with an average value of 1.54 m^2 m^{-2} (tab. 2). The relatively low mean value indicates that measured plots with lower LAI dominate. The lowest LAI was measured in a sink at the northern fringe of the field where the plant development was hindered by water logging. The highest LAI was determined in the field just outside a

drainless hollow in the centre of the field where optimized water availability with water logging resulted in a comparatively high LAI.
The hypothesis of this study was that binning of spectral bands may reduce data-inherent noise and consequently increase prediction accuracy. However, the resampled datasets achieve very similar results in LAI prediction. The LAI was predicted with an r^2_{cv} of 0.67 ($RMSE_{cv}$ = 0.40, RPD = 1.76) for all three data sets. Obviously, the different spectral resolution of 100, 150 and 300 spectral bands did not influence the modelling results. However, when analysing the results in details two samples with mean LAI were found to be overestimated disproportionately high.

	n = 37 samples			n = 35 samples (without outliers)		
Bands	r^2_{cv}	$RMSE^2_{cv}$	RPD	r^2_{cv}	$RMSE^2_{cv}$	RPD
100	0.669	0.403	1.763	0.904	0.222	3.275
150	o.669	0.404	1.762	0.905	0.221	3.294
300	0.670	0.403	1.764	0.917	0.207	3.522

Table 1. Results of PLS regression (cross-validation) of winter wheat LAI

Estimating the LAI of the wheat stands based on the remaining 35 samples enhanced prediction accuracies substantially (tab. 1). For all data sets of the three spectral resolutions (100, 150 and 300 bands) the cross-validated r^2 was higher than 0.9. While results for 100 and 150 spectral bands (0.904 and 0.905) turned out to be very similar, the prediction accuracy for 300 spectral bands in comparison was found to be higher resulting in an r^2_{cv} of 0.917 ($RMSE_{cv}$: 0.207) while the RPD increased from 3.29 to 3.52. In all cases the RPD was much higher than 2.0, which can be interpreted as an indicator for robust regression models (Dunn et al., 2002).
Although the PLSR model based on 300 spectral bands performed slightly better, it was decided to use the PLSR model with just 100 spectral bands for spatial analysis. It is assumed that the better model performance with 300 bands has to be attributed to random noise in the spectral measurements and not to significant spectral information.

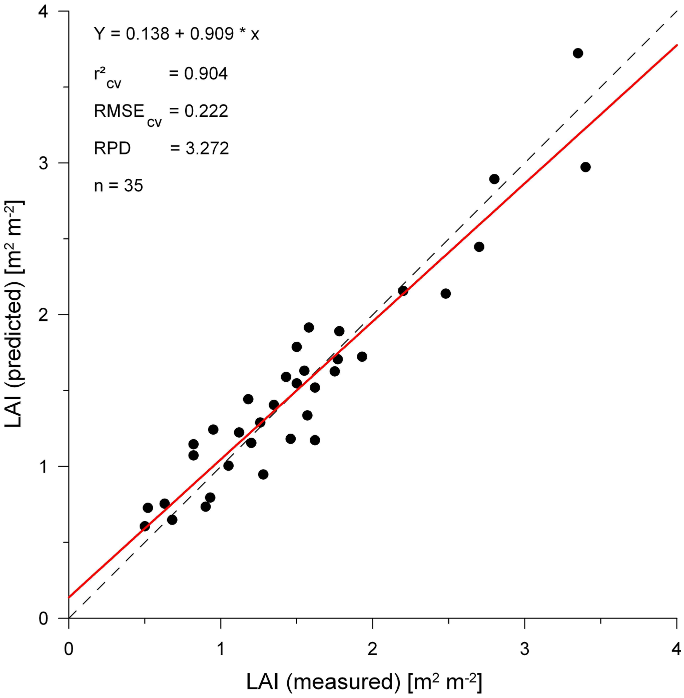

Figure 2. Scatterplot of predicted versus measured LAI for winter wheat based on PLSR. The solid red line represents the regression line while the dashed black line represents the 1:1-line.

As illustrated in figure 2, the offset observed for the estimation of wheat LAI was small, and the regression line between predicted and measured LAI was close to the 1:1-line, which indicates the models performances to be high and suitable for mapping application. Highest over- or underestimation were less than half a LAI unit (0.45 m^2/m^2 and -0.37 m^2/m^2, respectively). Residuals were found to be normal distributed and the mean was not significantly differing from zero.
Subsequently, the developed PLS-model using 100 spectral bands was applied to the AISA-DUAL data (fig. 3). Predicted LAI obtained from hyperspectral imagery were well in line with in-situ LAI measurements and represented the spatial inner-field variations. While deviations in means between predicted LAI and measured LAI are relatively low and deviations in minima are negligible, differences in maxima are relatively high (predicted: 4.04 m^2/m^2, field: 3.4 m^2/m^2) (tab. 2). These differences in maxima are resulting from the fact that in the field winter wheat stands with highest LAI obviously were not sampled (compare fig. 1 to fig. 3).

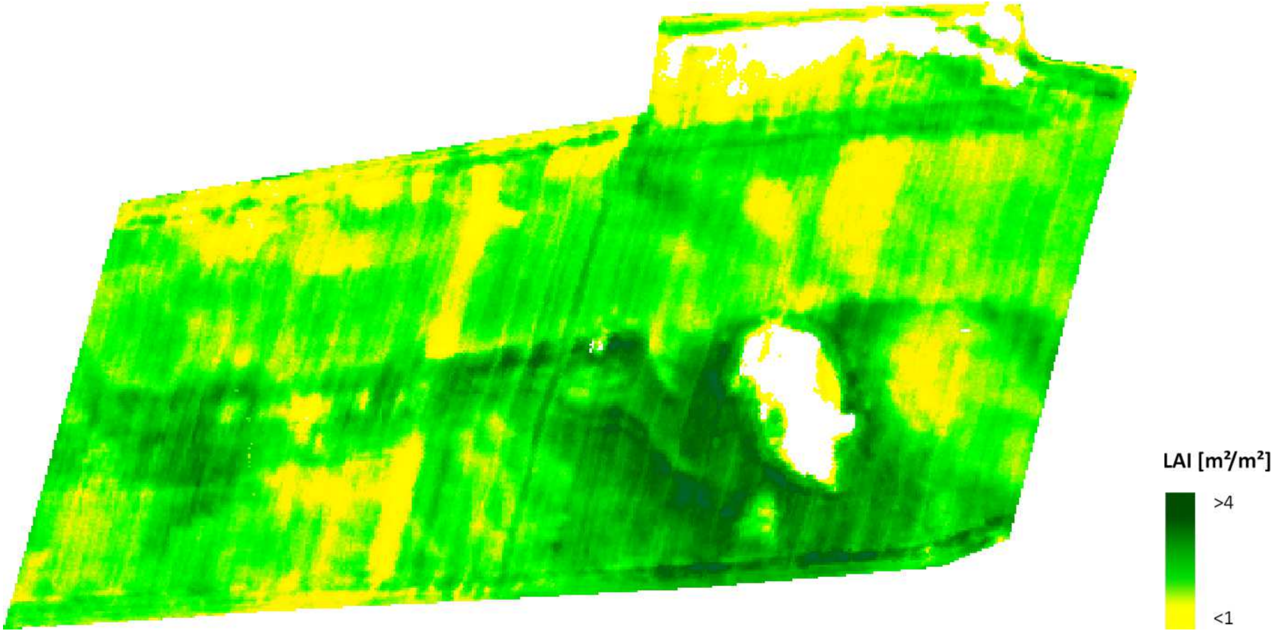

Figure 3. Wheat LAI predicted from AISA-DUAL hyperspectral imagery (white: no LAI)

Estimated winter wheat LAI clearly reflected site-specific natural conditions and geomorphologic settings. In general, the year 2011 was characterised by relatively dry weather conditions because of less precipitation limiting wheat plant development and resulting in low LAI. Lowest LAI values were predicted mainly in the northern area. Further on, low LAI values were estimated for the eastern part of the field which is characterized by sandy and gravelly soils resulting in insufficient water availability and penetration. In the south-eastern part of the field and at the northeast fringe areas are located (white) with no crop growth and hence no LAI. These areas are representing sinks which were flooded during winter and early spring resulting in crop dieback. No wheat plants were growing in these areas. High LAI above 3.5 m^2 m^{-2} primarily occurred in the south-eastern part of the field west closely to the area of no values. The reason might be an optimal water supply due to lateral water flow at the edge of the sink. Additionally, high LAI values were predicted at the southern fringe of the field which might be a result from double seeding on headlands.

predicted for all image pixel (n = 88,788)				measured in the field (n = 35)			
min	max^2_{cv}	mean	std. dev.	min	max^2_{cv}	mean	std. dev.
0.39	4.04	1.70	0.66	0.50	3.40	1.54	0.71

Table 2. Descriptive statistics of predicted and measured winter wheat LAI

5. CONCLUSIONS

Results clearly highlight the potential of hyperspectral imagery for the spatial assessment of wheat LAI and provide a suitable alternative for the conventional, often inaccurate, methods to describe the LAI using physiological development approaches. At the same time results raise the question how many spectral bands are needed for robust parameter estimation. Although the binning of AISA-DUAL data from 300 to 100 spectral bands resulted in an increase of the signal-noise-ratio, no significant difference in results of PLSR models were obtained. A reduction of spectral bands during sensor calibration would minimize recorded data volume and data processing time significantly.

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