COMPARISON OF NARROW BAND VEGETATION INDICES AND EMPIRICAL MODELS FROM HYPERSPECTRAL REMOTE SENSING DATA FOR THE ASSESSMENT OF WHEAT NITROGEN CONCENTRATION

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ABSTRACT:

The precise assessment of canopy nitrogen status is one of the key parameters in agriculture for high accuracy yield estimations. The increasing availability of airborne imaging hyperspectral sensors (e.g. HyMap, HySpex, CASI, AISA) provides the required data to derive canopy nitrogen status for large agricultural areas with a high spatial resolution. In this study the potential of vegetation indices – red edge inflection point, normalized difference red edge index and normalized difference nitrogen index – and empirical regression models – support vector regression, partial least squares regression – have been compared for the prediction of biomass nitrogen concentration of wheat from AISA-DUAL data. For empirical regression models the best result was found for support vector regression (r^2_{cv}=0.86, $RMSE_{cv}$=0.25, RPD=2.52) while the best result for vegetation indices was found for red edge inflection point (r^2_{cv}=0.69, $RMSE_{cv}$=0.35, RPD=1.83). The comparison proves a higher potential of empirical regression models to deliver predictions for biomass nitrogen concentration of wheat. The transfer of the SVR model to the AISA-DUAL data allowed to map the spatial distribution of N concentration with reasonable accuracy and reflected the spatial pattern of N of the investigated fields very well.

1. INTRODUCTION

Nitrogen is one of the most important crop limiting factors and a key parameter for crop monitoring and yield estimation in precision farming (Vigneau et al., 2011). Therefore, the assessment and mapping of total canopy nitrogen (N) content of agricultural crops is very important to optimize nitrogen fertilizer management in agronomy. An efficient and precise use of N-fertilizer is helpful to improve yield, reduce costs and lower environmental pollution at the same time (Ju et al., 2009).

Spectral reflectance of plants in the visible (VIS) and near infrared (NIR) region of the electromagnetic spectrum is primarily affected by plant pigments (e.g. chlorophyll) and cellular structure of the leaves. Plants with limited N-uptake will have a lower chlorophyll concentration which is an indicator for non-optimal photosynthesis (Clevers & Kooistra, 2012). In this context, hyperspectral remote sensing data showed already a high potential for the spatial and non destructive estimation of chlorophyll- and N-concentration. The availability of airborne hyperspectral imaging systems (e.g. HyMap, HySpex, AISA and CASI) in the last years allows acquiring data with high spatial and spectral resolution, supporting the fast assessment of N-status from agricultural fields (Jarmer & Vohland, 2011; Dorigo et al., 2007; Kokaly, 2001).

In this study the performance of narrow band vegetation indices and empirical regression methods derived from hyperspectral AISA-DUAL data is comparative investigated to retrieve detailed information about the spatial distribution of N-concentration from wheat field in Germany.

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2. STUDY AREA AND DATA

2.1 Study Area

The study area (11°54′E, 51°47′N) is located in the eastern part of Germany in the federal state of Saxony-Anhalt (Fig. 1) and intensively used for agriculture. The region is characterized by a slightly undulated tertiary plain with an altitude of 70 m above sea level that is covered by a thin Loess layer up to 1.2 m deep. The study area is situated in the rain shadow of the Harz Mountains. For that reason the region is distinctly dry with 430 mm mean annual precipitation. The mean annual temperature is between 8 and 9°C. Chernozem in conjunction with Cambisols and Luvisols is the predominant soil type of the Loess covered Tertiary plain. The test site is characterized by highly diverse soil properties, resulting in fine-scale pattern of soil texture and organic matter. Within the study area a wheat field with a size of 90 ha was selected for the assessment of wheat nitrogen concentration.

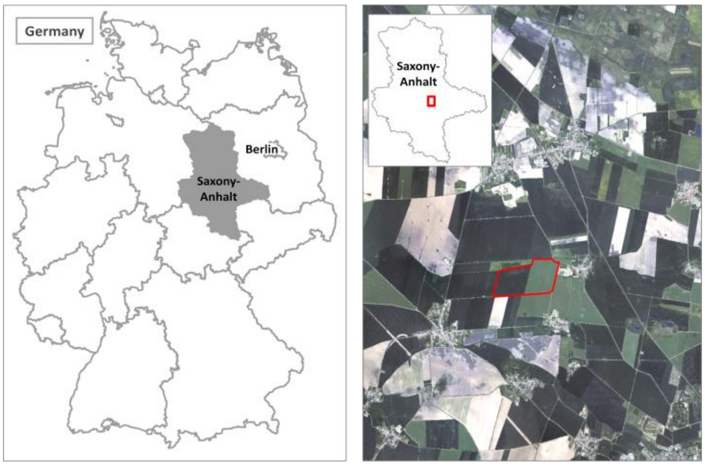

Figure 1. Location of the test site with the investigated wheat field in the federal state Saxony-Anhalt in Germany

2.2 Data and Materials

For the spatial assessment of N-concentration hyperspectral data of the airborne system AISA-DUAL (Specim, Ltd.) was used. AISA-DUAL is a hyperspectral pushbroom scanner consisting of the two separate sensors, AISA-EAGLE (VIS/NIR, 400-1000 nm) and AISA-HAWK (SWIR, 1000-2500 nm). The AISA-DUAL imagery of the test site was acquired on the 10th of May 2011. The image data have a geometric resolution of 3 m in 367 spectral bands in the wavelength range of 400-2500 nm. For the data correction the ROME destriping algorithm (Rogaß et al., 2011) was used to reduce miscalibration effects, present as deficient lines along track in the images. For the following atmospheric correction the software Fast Line-of-sight Atmospheric Analysis of spectral Hyper cubes (FLAASH) was used. Additionally, an empirical line correction was made with spectral ground measurements of different dark and bright targets collected in the test site during the time of AISA-DUAL data acquisition (Smith & Milton, 1999). The geometric correction of the AISA-DUAL data was realized with the software CaliGeo and orthorectification was performed with the software ENVI.

For covering the entire value range of wheat N-concentration satellite data of former years were used to develop an adjusted strategy to get a representative sampling for the investigated field. In this context, plant samples of the above-ground biomass of 37 plots (each with a size of 50 x 50 cm) were harvested completely on the 7th and 8th of May 2011 (Fig. 2). Afterwards the plant material was dried in a drying oven. Subsequently, the N-concentration of the plant dry matter of each plot was determined in the laboratory using an elemental analyser (Elementar Analysensysteme GmbH). Furthermore, two drainless hollows in the southeast and north part of the field showing no vegetation cover as a result of waterlogging in early spring 2011 were masked by building a decision tree based on normalized difference vegetation index (NDVI).

3. METHODS

3.1 Spectral Binning

The spectral signatures of the processed AISA-DUAL pixels showed a high level of noise. For the reduction of noise a spectral binning was made on the AISA-DUAL data. Spectral binning is a commonly used method to reduce noise in hyperspectral data. In this context adjacent spectral bands were 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). Therefore, three adjacent spectral bands of the AISA-DUAL data were averaged to generate one new spectral band. Thus, the number of spectral bands was reduced from 367 to 122 and the SNR of the AISA-DUAL data could be improved. Furthermore, 22 spectral bands in the range of the water vapor 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 because of the high noise in this spectral regions of the AISA- DUAL system leaving 100 spectral bands for further analysis.

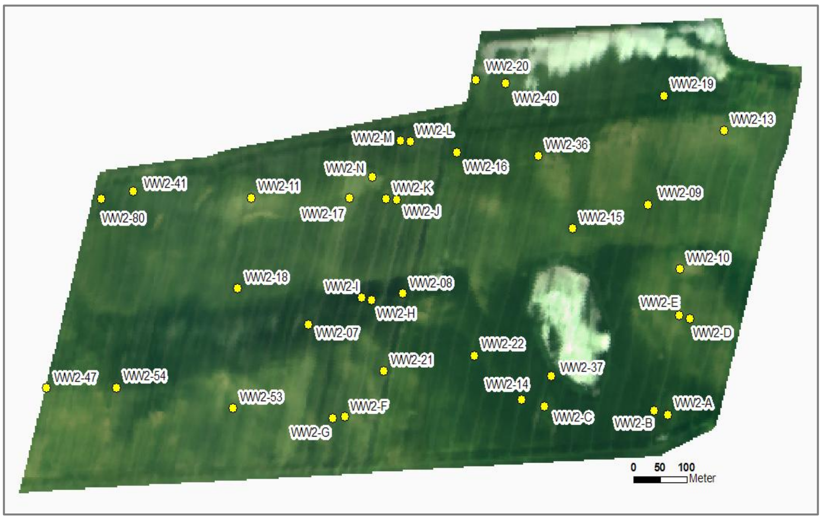

Figure 2. Investigated field with the location of the wheat plots (background: AISA-DUAL data in RGB 635 nm, 552 nm, 458 nm)

3.2 Narrow Band Vegetation Indices

The narrow band vegetation indices (VI) red edge inflection point (REIP), normalized difference red edge index (NDRE) and normalized difference nitrogen index (NDNI) were calculated for the AISA-DUAL data of the investigated field (Tab. 1). Subsequently, the index values of the pixels were extracted at the geographic location of the 37 wheat plots and linear regression models were calculated between the pixel values and the N-concentration of the wheat plots. For accuracy assessment the results were cross-validated (cv) with the 'leave-one-out-method' and the coefficient of determination (r^2_{cv}) and the root mean square error ($RMSE_{cv}$) were derived for the predictions. Furthermore, the ratio between standard deviation of the measured values and the $RMSE_{cv}$ (RPD) was chosen as an additional measure of the estimation accuracy (Malley et al., 2004).

Narrow Band VI	Formula	Range
REIP (Guyot et al., 1988)	$700 + 40 * [\left(\frac{(\lambda_{670}+\lambda_{780})}{2} - \lambda_{700}\right) / (\lambda_{740} - \lambda_{700})]$	700 nm - 760 nm
NDRE (Barnes et al., 2000)	$(\lambda_{790} - \lambda_{720}) / (\lambda_{790} + \lambda_{720})$	- 1 - + 1
NDNI (Serano et al., 2002)	$[\log\left(\frac{1}{\lambda_{1510}}\right) - \log\left(\frac{1}{\lambda_{1680}}\right)] / [\log\left(\frac{1}{\lambda_{1510}}\right) + \log\left(\frac{1}{\lambda_{1680}}\right)]$	- 1 - + 1

Table 1. Narrow Band Vegetation Indices, formulas and value ranges

where λ = wavelength in nm

3.3 Empirical Models

Two empirical-statistical algorithms, support vector regression (SVR) and partial least squares regression (PLSR), were applied for the spatial assessment of wheat N-concentration. The spectral signatures of the image pixels corresponding to the geographic location of the different wheat plots were extracted from the AISA-DUAL data. Afterwards a PLSR model built from the extracted spectral signatures and the N-concentration of the wheat plots has been set up with the software 'autopls' (Schmidtlein et al., 2012). Additionally, a SVR model was built with the same data using the software 'ImageSVM' (Rabe et al., 2009). Both software products are freely available and can be used as part of the EnMAP-Box (www.enmap.org). Subsequently, both empirical models have been applied to AISA-DUAL image data of the wheat field to map the spatial distribution of N concentration. The results of PLSR and SVR were cross-validated with the 'leave-one-out-method'. Finally, the same statistical values as for the results of the indices (r^2_{cv}, $RMSE_{cv}$ and RPD) were calculated to check the accuracy of the empirical model results.

4. RESULTS AND DISCUSSION

The investigated wheat plots covered an N-concentration range from 1.28% at minimum and 4.13% at maximum (Tab. 2). Substantial spatial variations could be found within the investigated field which is an indicator for large differences regarding the spatial N-concentration distribution.

n	Min	Max	Mean	SD
37	1.28	4.13	2.07	0.64

Table 2. Descriptive statistics of wheat plot N-concentration in %

The different vegetation indices were calculated and linear regression models were built to predict N-concentration values of the vegetation index pixel corresponding to the geographic location of the wheat samples. The results show that the indices are not eligible to predict the N-concentration of wheat with sufficient accuracy. With a r^2_{cv} of 0.69 and $RMSE_{cv}$ of 3.50 the REIP provides the best result closely followed by the NDRE (r^2_{cv} = 0.68, $RMSE_{cv}$ = 3.58). Compared to the other indices the result for NDNI shows very low accuracy (r^2_{cv} = 0.45, $RMSE_{cv}$ = 4.70). Furthermore, the RPD of all indices have values lower than 2, which indicates a deficient calibration of the models (Dunn et al., 2002).

	n	**r^2_{cv}**	**$RMSE_{cv}$**	**RPD**
REIP	37	0.69	0.35	1.83
NDRE	37	0.68	0.36	1.80
NDNI	37	0.45	0.47	1.37

Table 3. Results of the narrow band vegetation indices

Additionally to the indices SVR and PLSR were used to predict the N-concentration of the wheat plots from AISA-Dual data. The result of SVR modeling shows that N-concentration was predicted with higher accuracy (r^2_{cv}=0.86, $RMSE_{cv}$ = 0.26). The RPD value of 2.46 is above 2 and indicates a successful calibration of the model. PLSR provides a result on a lower level of accuracy compared to SVR. The r^2_{cv} has entirely a value of 0.75, RPD value is 2 and the $RMSE_{cv}$ with 0.32 is higher.

	n	**r^2_{cv}**	**$RMSE_{cv}$**	**RPD**
PLSR	37	0.75	0.32	2.00
SVR	37	0.86	0.26	2.52

Table 4. Results of the empirical models

Figure 3 illustrates the scatter plots of the REIP and the SVR model. Both models show a slight over fitting of lower and a distinct under fitting of higher N-concentration for the predicted values. Finally, the models were transferred to the AISA-DUAL image date to predict the spatial distribution of N for the entire field (Fig. 4). The predicted images from REIP and SVR show similar spatial patterns of the field but significant differences in N-concentration range. The REIP model overestimates higher- and underestimates lower N-concentrations for the entire field more than the SVR model. However, SVR provides results which cover the range of N-concentration measured in field. The highest N-concentrations were measured around the drainless hollow in the southeast of the field. Therefore, a reason could be the optimal supply of water because of the waterlogging in early spring 2011. The SVR prediction image shows the highest concentrations of N at this location of the field. Furthermore, the lowest N-values were measured at the eastern edge of the field. This part of the field is characterized by sandy and gravelly soils which results in insufficient water availability and root penetration. For these areas the SVR image shows low values, too. A general problem in 2011 were the relatively dry weather conditions because of less precipitation. The absorption of the nitrogenous fertilizers was possible only with difficulty because plants can only absorb nitrogen dissolved in water.

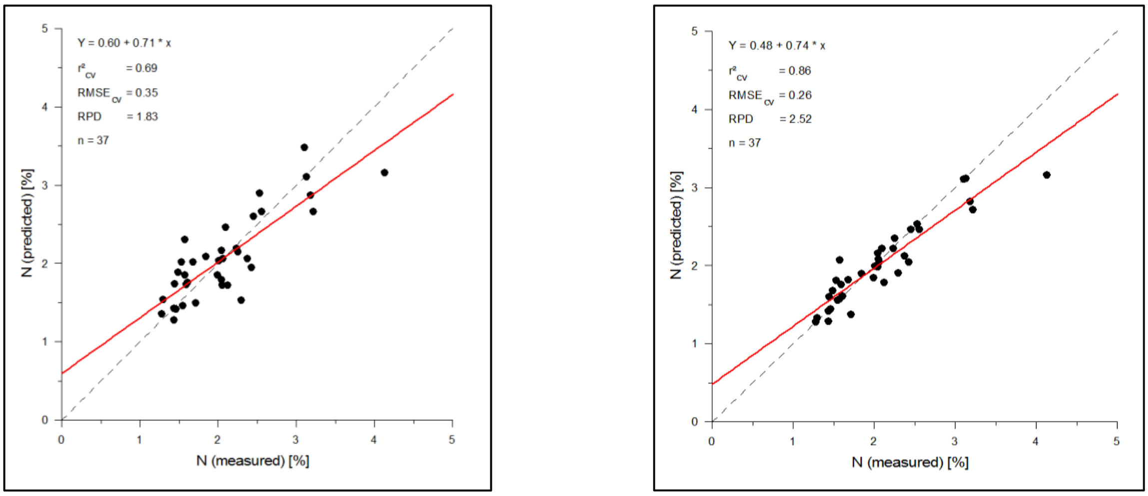

Figure 3. Scatter plot of the REIP model (left) and the SVR model (right) for predicting N-content from AISA-DUAL data

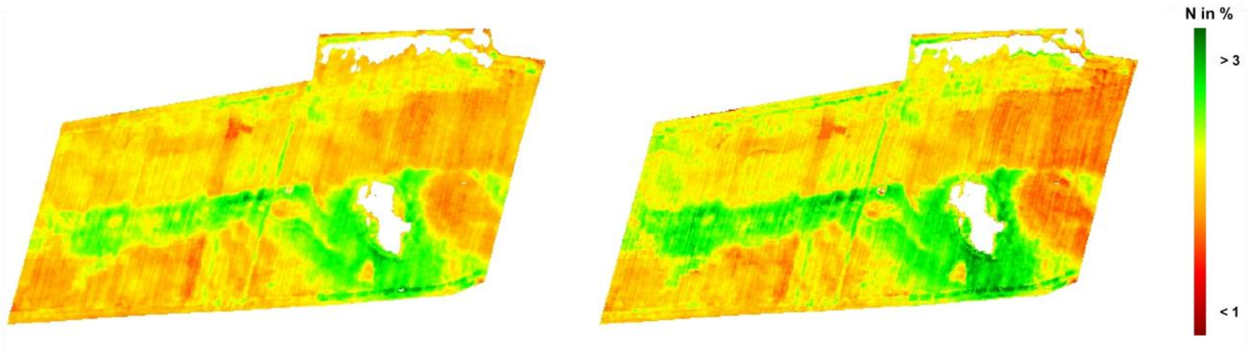

Figure 4. Spatial distribution of N-concentration predicted by REIP (left) and SVR (right), white = no data values

5. CONCLUSION

The comparative investigation of empirical regression models and narrow band vegetation indices for the estimation of wheat canopy N-concentration showed that empirical regression models provide more accurate results compared to the tested vegetation indices. The prediction result from AISA-DUAL data by SVR was very reliable and more precise than the result of the PLSR. On the contrary, the calculated narrow band vegetation indices delivered results with less accuracy. REIP and NDRE showed only limited prediction capabilities for the estimation of canopy N-concentration. The NDNI in this study seemed to be completely ineligibly for the prediction of wheat N-concentration. The result indicated the importance of the red edge spectral region because REIP and NDRE are based on this part of the electromagnetic spectrum while the NDNI only uses spectral information from the short wave infrared.

The transfer of the SVR model to AISA-DUAL imagery allowed to assess spatial distribution of N-concentration with reasonable accuracy and reflected the spatial pattern of the investigated field very well. The concentration range obtained from the hyperspectral image data for the investigated wheat field agreed well with laboratory analysis. The results of the study indicate the high potential of SVR for N-concentration prediction from hyperspectral data on inner field scale.

For further investigations additional wheat samples, their dry matter and measured N-concentration values from a campaign in 2012 will be included to extend the value range of N for building more robust regression models and to assess the spatial N-content of wheat. Furthermore, it has to be investigated more precisely which spectral region is suitable for nitrogen modeling. This information is important for the development of new and less expensive sensors in precision agriculture which only need small parts of the electromagnetic spectrum to derive N-concentration in real-time for fertilization and yield quality estimations with high spatial and temporal resolution.

6. REFERENCES

Barnes, E.M., T.R. Clarke, S.E. Richards, P.D. Colaizzi, J. Haberland, M., Kostrzewski, P. Waller, C. Choi, E. Riley, T. Thompson, R.J. Lascano, H. Li, and Moran M. S., 2000. Coincident detection of crop water stress, nitrogen status and canopy density using ground-based multispectral data [CD ROM]. In P.C. Robert et al. (ed.) Proc. Int. Conf. Prec. Agric., 5th, Bloomington, MN. 16–19 July 2000. ASA, CSSA, and SSSA, Madison, WI.

Clevers, J.G.P.W. and Kooistra, L. 2012. Using Hyperspectral RemoteSensing Data for Retrieving Canopy Chlorophyll and Nitrogen Content. *IEEE Journal of Selected Topics in Applied Earth Observation and Remote Sensing*, 5(2), pp. 574-583.

Dell'Endice, F., Nieke, J., Koetz, B., Schaepman, M.E. and Itten, K., 2009. Improving radiometry of imaging spectrometers by using programmable spectral regions of interest. *ISPRS Journal of Photogrammetry and Remote Sensing*, 64(6), pp. 632-639.

Dunn, B.W., Beecher, H.G., Batten, G.D. and Ciavarella, S., 2002. The potential of near-infrared reflectance spectroscopy for soil analysis. A case study from the Riverine Plain of south-eastern Australia. *Australian Journal of Experimental Agriculture,* 42 (5), pp. 607-614.

Dorigo, W.A., Zurita-Milla, R., de Wit, A.J.W., Brazile, J., Singh, R. and Schaepman, M.E., 2007. A review on reflective remote sensing and data assimilation techniques for enhanced agroecosystem modeling. *International Journal of Applied Earth Observation and Geoinformation*, 9, pp. 165–193.

Guyot, G., Baret, F., and Major, D. J., 1988. High spectral resolution: Determination of spectral shifts between the red and infrared. *International Archives of Photogrammetry and Remote Sensing*, 11, pp. 750–760.

Jarmer, T. and Vohland, M., 2011. Spectroscopy and hyperspectral imagery for nitrogen as-sessment of summer barley. *Proceedings of the EARSeL 7th SIG-Imaging Spectroscopy Workshop*, Edinburgh, April 11-13th 2011.

Ju, X.-T., Xing, G.-X., Chen, X.-P., Zhang, S.-L., Zhang, L.-J., Liu, X.-J., Cui, Z.-L., Bin, Y., Christie, P., Zhu, Z.-L. and Zhang, F.-U., 2009. Reducing environmental risk by improving N management in intensive Chinese agricultural systems. *Proceedings of the National Academy of Sciences*, 106, pp. 3041-3046.

Kokaly, R.F., 2001. Investigating a physical basis for spectroscopic estimates of leaf nitrogen concentration. *Remote Sensing of Environment*, 7, pp. 153-161.

Malley, D.F., Martin,P.D. and Ben-Dor, E., 2004. Application in analysis of soils. *Nearinfrared spectroscopy in agricultur*, 44, pp. 729-783.

Mevik, B. H., Wehrens, R., 2007. The pls Package: Principal Component and Partial Least Squares Regression in R. *Journal of Statistical Software*, 18(2), pp. 1-24.

Rabe, A., van der Linden, S. and Hostert, P., 2009. Simplifying Support Vector Machines for Regression Analysis Of Hyperspectral Imagery. *Hyperspectral Image and Signal Processing: Evolution in Remote Sensing. WHISPERS '09. First Workshop on Signal Processing & Analysis.* Grenoble, August 26-28th 2009.

Rogaß, C., Spengler, D., Bochow, M., Segl, K., Lausch, A., Doktor, D., Roessner, S., Behling, R., Wetzel, H.U. and Kaufmann, H., 2011. Reduction of Radiometric Miscalibration-Application to Pushbroom Sensors. *Sensors*, 11, pp. 6370-6395.

Schmidtlein S., Feilhauer H. and Bruelheide H., 2012. Mapping plant strategy types using remote sensing. *Journal of Vegetation Science*, 23, pp. 395-405.

Serano, L., Peñuelas, J. And Ustin, S.L., 2002. Remote sensing of nitrogen and lignin in Mediterranean vegetation from AVIRIS data: Decomposing biochemical from structural signals. *Remote Sensing of Environment*, 81, pp. 355-364.

Smith, G.M. and Milton, E.J., 1999. The use of the empirical line method to calibrate remotely sensed data to reflectance. *International Journal of Remote Sensing*, 20(13), pp. 2653-2662.

Vigneau, N., Ecarnot, M., Rabatel, G. and Roumet, P., 2011. Potential of field hyperspectral imaging as a non destructive method to assess leaf nitrogen content in Wheat. *Field Crops Research*, 122(1), pp. 25-31.

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