WETLAND LEAF AREA INDEX MODELLING WITH FIELD AND SATELLITE HYPERSPECTRAL DATA

Tomasz Berezowski[1,2], and Jarosław Chormański[1]

1. Department of Hydraulic Structures, Warsaw University of Life Sciences, Nowoursynowska 166, 02-787 Warsaw, Poland; j.chormanski(at)levis.sggw.pl
2. Department of Hydrology and Hydraulic Engineering, Vrije Universiteit Brussel, Pleinlaan 2, 1050 Brussels, Belgium; t.berezowski(at)levis.sggw.pl

ABSTRACT

Leaf Area Index (*LAI*) is an important variable in environmental processes modelling. Already several approaches were proposed to model wetlands *LAI* with remote sensing data. However, none of these methods was based on upscaling the field spectral reflectance measurements, which is a matter of this paper. In this study, we used combined measurements of spectral reflectance (350-2500 nm) and *LAI* to establish a regression model of *LAI*. The spectral reflectance was resampled to the spectral resolution of a satellite hyperspectral sensor (CHRIS-PROBA) beforehand and then used to calculate *NDVI*-based spectral indices. From the set of spectral indices the one with the strongest correlation with *LAI* was chosen for the regression. Finally, the regression was applied to the CHRIS satellite images and the results were analysed within the scope of different wetland communities of the study area. The results show that the optimal regression model gives statistically different *LAI* values for the majority of different ground truth plant communities, rivers and urban areas.

INTRODUCTION

Leaf Area Index, *LAI* (m^2 m^{-2}), expresses leaves area per the unit canopy area in the top projection and is an important parameter in environmental modelling. Spatial maps of *LAI* are used in estimating hydrological processes and variables: evapotranspiration (1), hydrological modelling (2,3), radiative transfer models (4) and many others.

Nowadays, the *LAI* mapping involves mostly remote sensing techniques. Certainly the most popular approach is to develop a regression between pixel values of satellite imagery and georeferenced *LAI* measurements. In the regression approach, both optical (5,6) and microwave sensors (7,8) are successfully used. This method gives a straightforward way for *LAI* mapping, but requires distributed spatial sampling to obtain acceptable results.

Another popular approach is to develop a regression between spectral properties (e.g., reflectance) sampled in the field and measured *LAI* at the same spots. This method is popular for *LAI* estimation of individual species, mostly crops (9). Some of the studies using the latter approach establish the regression using the same bands as available in the satellite sensors (10,11) to show the potential of upscaling the results with satellite images.

The aim of this paper is to establish a regression between *LAI* and spectral indices calculated with field spectroscopy data. The regression is validated on a multispecies data set reflecting the true species composition in the study area. Finally, a regression equation is used to calculate a *LAI* map derived from the CHRIS PROBA hyperspectral image of the study area.

METHODS

Study area

The study is conducted in the Biebrza National Park (BNP). The BNP which preserves the biggest wetland area in West and Central Europe is situated in north-east Poland. The Biebrza wetland consists of three basins: Upper, Middle and Lower Basin. As a study area we selected the Upper

DOI: 10.12760/02-2014-1-06

Basin of the Biebrza wetlands. Important factors influencing ecosystem development in the Upper Basin are groundwater seepage and flooding, which occur almost every year after a spring thaw (12). The field survey is made in different herbaceous ecosystems characteristic of the study area and interesting with regard to their water storage capacity (13). They were grouped in three types: a) sedge communities with a management policy, mowed once/twice a year; b) sedge communities not mowed for the last 10-20 years, and c) moss-sedge ecosystem mowed twice a year (Figure 1).

Figure 1: The three types of sedge communities dominant in the study area.

Field measurements and processing

The sampling points of the field measurements were distributed in the river valley of the Upper Biebrza Basin (Figure 2). The field measurements were the same at each sampling point and consisted of: spectral reflectance (ASD FieldSpec 3, measurement range 350-2500 nm), *LAI* (LI-COR LAI 2000) and geographical coordinates (GPS receiver). The measurements campaigns were conducted two times: 27-28 June 2011 and 29 June 2012. The differences in phenological cycle between the two measurement campaign dates provided more representative data sources for regression analysis and model application.

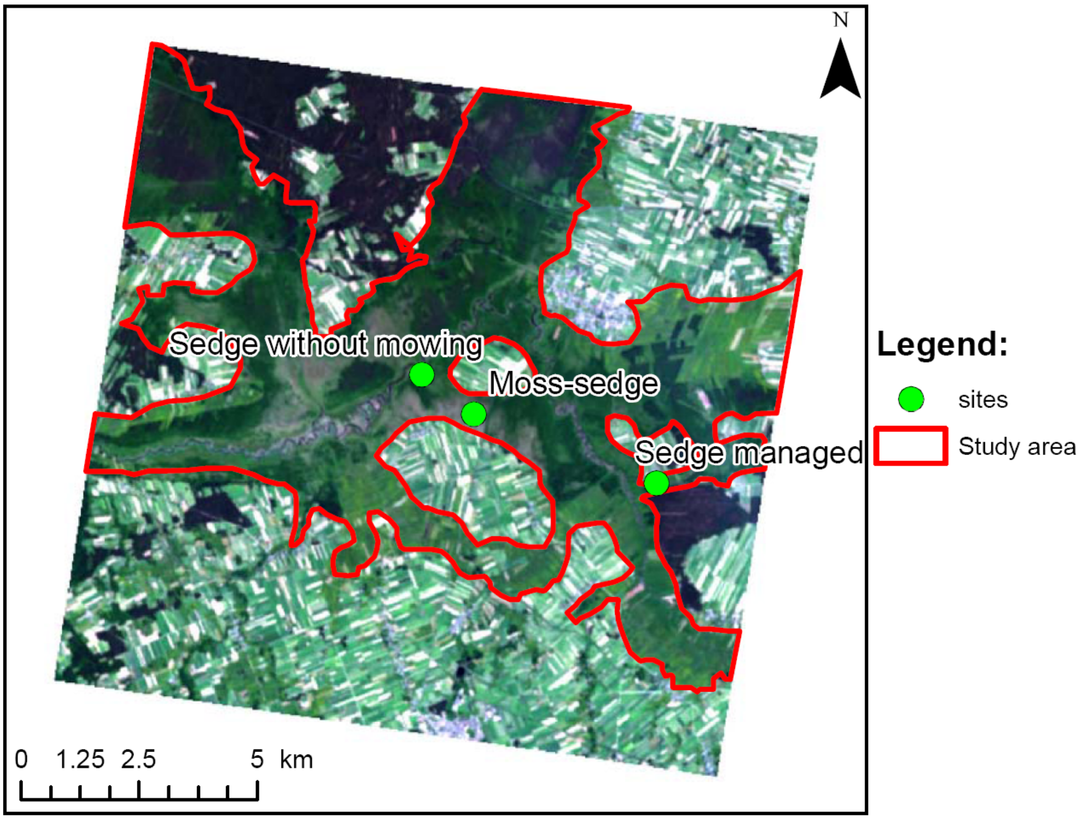

Figure 2: General location of the measurement sites in the study area. The background is the true colour composite based on CHRIS image bands.

In order to account for heterogeneity in the sensitivity of the spectroradiometer (ASD instrument) field-of-view (FOV) the samples were acquired at several angles from the main axis; several repetitions were made at each measurement point in order to obtain representative samples. The spectral reflectance was recalculated from the original resolution to the CHRIS sensor bands using the CHRIS spectral response function. The *LAI* measurements were taken in 10 repetitions at each spot at approximately the same area as the spectroradiometer FOV.

The field measurement data set was randomly divided into validation and calibration samples prior to further processing. The spectral reflectance recalculated to the CHRIS bands was further used to calculate normalised-difference spectral indices, which have a general form similar to the *NDVI*:

$$i_{b1\_b2} = \frac{b1 - b2}{b1 + b2}$$

where *b1* and *b2* are reflectances for selected CHRIS bands. The i_{b1_b2} values were calculated for all possible compositions of the 62 CHRIS bands. The optimum i_{b1_b2}, used to establish the regression with *LAI*, was selected based on the strongest correlation with the measured *LAI*. The quality of the regression was evaluated based on the independent validation sample. The regression model was based on a power law in the general form: $LAI = a \cdot i_{b1\_b2}{}^{n}$, where a and n are parameters estimated with the nonlinear least squares method.

Satellite remote sensing data

The CHRIS image (background in Figure 2), was acquired on 4 June 2011. In mode 1, the CHRIS image has 62 bands, ~10 nm widths, from 415 to 1003 nm, at 34 m spatial resolution. For our experiment only the nadir CHRIS image was used. Standard pre-processing methods of noise removal were applied and the CHRIS image was registered with ground control points at 30 m spatial resolution. The image was converted from radiance to surface reflectance by an empirical line method using the reference spectra sampled in the study area.

RESULTS

In all, 43 samples of *LAI* and spectral reflectance were taken. After a random division the calibration sample consisted of 22 and the validation of 21 measurements. The strongest correlation between i_{b1_b2} and *LAI* was found for the CHRIS bands 52 (886 nm) and 11 (530 nm) (Figure 3); from the two possible combinations of *b52* and *b11*, the combination with positive correlation (i_{52_11}) was selected for the identification of the regression model (Figure 3). The band 530 nm is unusual for the *NDVI* calculation, as it belongs to the green part of the spectrum. However, the 530 nm band is used to calculate the photochemical reflectance index (*PRI*), which can be related to *LAI* (14) as well as to the red and NIR bands.

The regression equation using i_{52_11} to model *LAI* took the form: $LAI = 14.508 \cdot i_{52\_11}{}^{6.245}$. The fitted model and validation are presented in Figure 4. The validation reveals r^2=0.697, which is a good score for multispecies composition *LAI* models. Moreover, the mean absolute error of the *LAI* model was only 0.84 (in *LAI* units), which is equivalent to 15% of the data range.

In the final step, the regression equation was used to calculate a map of *LAI* using the original bands of the CHRIS image (Figure 5). The average *LAI* in the analysed plant communities was: managed meadow – 2.23; unmanaged meadow – 2.08 and moss-sedge – 1.16. In the other landscape features, easy to delineate from the satellite image, the average *LAI* was: river and the bank vegetation – 0.64; urban and built-up areas – 0.09. The differences between average *LAI* for different plant communities of other landscape features are always bigger than 15% of the data range of the regression-based *LAI* map (Figure 5). Moreover, the *t*-test results calculated between these average values shows, that they are different at *p*-levels < 0.001 except between the managed and unmanaged meadows which have a *p*-level = 0.126.

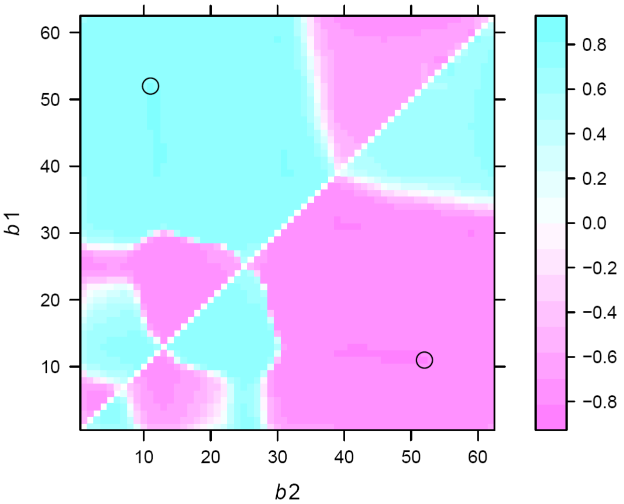

Figure 3: Correlation matrix for CHRIS i_{b1_b2} with measured LAI. The circles indicate the two possible combinations of b52 and b11 with the strongest correlation.

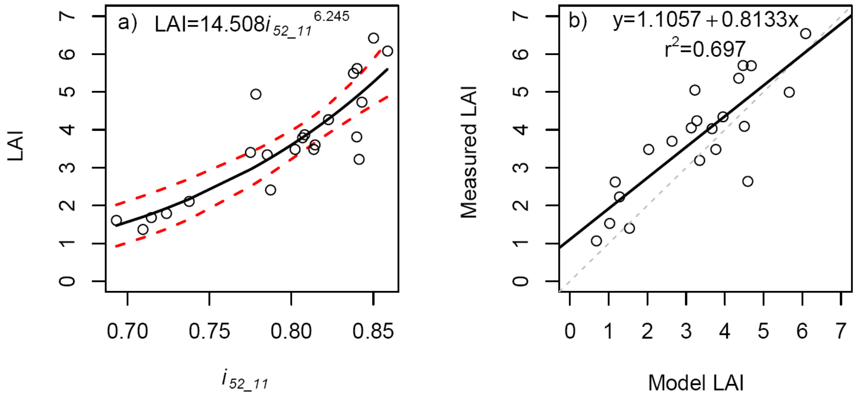

Figure 4: The power law model fitted to the calibration subsample of LAI measurements (a) and the independent validation of the model (b). The black lines follow the equations presented at the top of each plot; the dashed red lines present the 95% confidence interval for the fitted model; the dashed grey line is the 1:1 line.

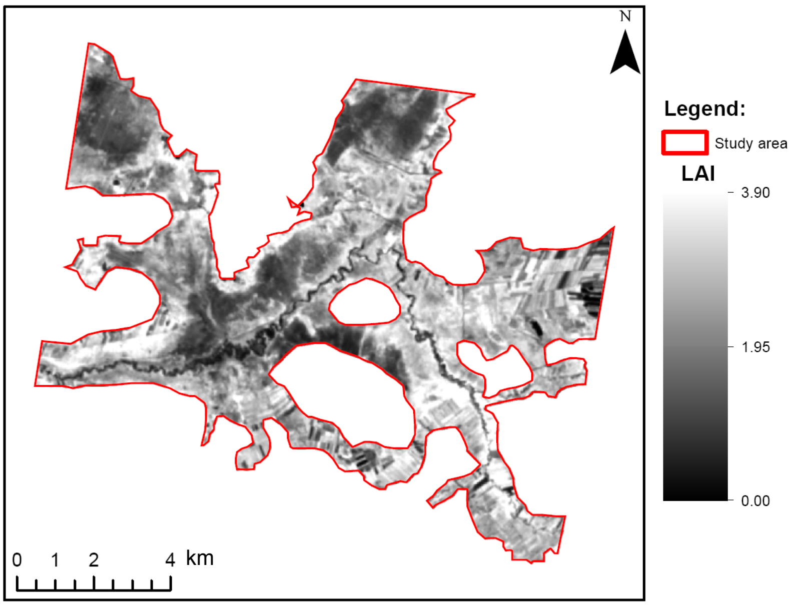

Figure 5: LAI map obtained from the CHRIS image and the regression established from field measurements.

The results show the expected variability in the landscape features of the Biebrza River valley. However, the data range of the *LAI* values is lower than the data range of measured *LAI* in the field campaigns. The reason is twofold: The satellite image was acquired about 1 month before the field campaigns, so the phenological cycle was in an earlier stage; the point measurements cannot be directly compared with pixel values which average the area of 30×30 m^2 and smooth the pixel values by mixing with surrounding objects. Nevertheless, the methodology described in this paper has a potential to be applied in other projects, if an additional spatial evaluation of the final product is conducted.

CONCLUSIONS

The presented methodology of estimating *LAI* from satellite images based on combined field measurements of *LAI* and spectral reflectance enables promising results to be generated. The validation of the regression model of *LAI* explained by field spectral reflectance resulted in a strong co-linearity with the observed *LAI* and errors lower than 20% of the data range. The *LAI* map obtained by applying the regression model to the hyperspectral satellite image shows the expected *LAI* variability in the analysed landscape features. However, *LAI* maps developed with the proposed method should be validated with *LAI* samples measured during the satellite image acquisition. As such *LAI* samples were not available in this research, we propose to perform a similar experiment with the mentioned validation step for further work.

ACKNOWLEDGEMENTS

The research was conducted partly within the scope of research grant NCN 2012/05/B/NZ9/03467 INterception-TRanspiration-EVaporation; interdependencies of hydrological processes in WETland ECOsystems (INTREV-WetEco).

REFERENCES

1 Szporak-Wasilewska S, J Szatyłowicz, T Okruszko & S Ignar, 2013. Application of the Surface Energy Balance System Model (SEBS) for mapping evapotranspiration of extensively used river valley with wetland vegetation. In: Towards Horizon 2020, edited by R Lasaponara, N Masini & M Biscione (EARSeL, 2013) 929-942

2 Chormański J & R Michałowski, 2011: Hydrological catchment model WetSpa-SGGW integrated with a calculation module in ArcGIS environment. Scientific Review – Engineering and Environmental Sciences, 53: 196-206 (in Polish language)

3 Zhou Y, Y Zhang, J Vaze, P Lane & S Xu, 2013. Improving runoff estimates using remote sensing vegetation data for bushfire impacted catchments. Agricultural and Forest Meteorology, 182-183(15): 332-341

4 Jarocińska A, 2014. Radiative Transfer Model parametrization for simulating the reflectance of meadow vegetation. Miscellanea Geographica, 18(2): 5-9

5 Zhou J-J, Z Zhao, J Zhao, Q Zhao, F Wang & H Wang, 2014. A comparison of three methods for estimating the LAI of black locust (*Robinia pseudoacacia L.*) plantations on the Loess Plateau, China. International Journal of Remote Sensing, 35: 171-188

6 Budzyńska M, K Dąbrowska-Zielińska, K Turlej, I Małek & M Bartold, 2011. Monitoring przyrodniczy Bagien Biebrzańskich z zastosowaniem Teledetekcji. Water-Environment-Rural Areas, 11(35): 39-64 (in Polish language)

7 Dabrowska-Zielinska K, M Budzynska, W Kowalik, I Małek, M Gatkowska, M Bartold & K Turlej, 2012. Biophysical parameters assessed from microwave and optical data. International Journal of Electronics and Telecommunications, 58(2): 99-104

8 Kumar V, M Kumari, S K Saha, 2013. Leaf area index estimation of lowland rice using semi-empirical backscattering model. Journal Of Applied Remote Sensing, 7(1): 073474

9 Zhang B, K Song, Y Zhang, F Li & Z Wang, 2005. Study on the relationship between hyper-spectral reflectance and soybean LAI, aboveground biomass. In: Geoscience and Remote Sensing Symposium, 2005. IGARSS '05 Proceedings. IEEE International (5): 3583-3586

10 Qian C, H Jingfeng, W Renchao & T Yanlin, 2003. Analyses of the correlation between rice LAI and simulated MODIS vegetation indices, red edge position. Transactions of the Chinese Society of Agricultural Engineering, 2003(5): 104-108

11 Gitelson A A, A Viña, T J Arkebauer, D C Rundquist, G Keydan & B Leavitt, 2003. Remote estimation of leaf area index and green leaf biomass in maize canopies. Geophysical Research Letters, 30(5): 1248

12 Chormański J, T Okruszko, S Ignar, O Batelaan, K T Rebel & M J Wassen, 2011. Flood mapping with remote sensing and hydrochemistry: A new method to distinguish the origin of flood water during floods, Ecological Engineering, 37: 1334-1349

13 Ignar S, A Węglewska, S Szporak-Wasilewska & J Chormański, 2013. Spatial and temporal variability of the interception in the natural wetland valley, the lower Biebrza basin case study, Annals of Warsaw University of Life Sciences – SGGW, Land Reclamation, 45(1): 111-116

14 Barton, C V M & P R J North, 2001. Remote sensing of canopy light use efficiency using the photochemical reflectance index: Model and sensitivity analysis. Remote Sensing of Environment, 78(3): 264-273