Prediction of Leaf Area Index using Integration of the Thermal Infrared and Visible-short Wave Infrared Data over the Mixed Temperate Forest

❖ Introduction

The retrival of leaf area index (LAI) as one of the essential biodiversity variable from remote sensing data has shown to be successful over visible/near-infrared (VNIR, 0.3-1.0 µm), shortwave infrared (SWIR, 1.0-2.5 µm), and TIR (8-14 µm) domains. However, the integration of VNIR/SWIR with the TIR (land surface emissivity, LSE) data for LAI estimation has not been addressed yet. In this respect, the utility of Landsat-8 TIR data together with its VNIR/SWIR spectral data was examined to quantify LAI over Bavarian Forest National Park (Mixed temperate forest) in Germany.

❖ Research Objective

This study aims to assess the potential of the integration of the VNIR/SWIR and TIR data to predict LAI. The specific research objective of this study is:

- To investigate the retrieval of LAI by means of VNIR/SWIR and TIR data, using artificial neural networks as a machine learning approach.

❖ Materials and methods

• Collection of in situ structural canopy parameters

Field measurements were performed over the Bavarian Forest National Park, which is located in the federal state of Bayern, in the southeastern part of Germany, along the border with the Czech Republic (49˚ 3′ 19″ N, 13˚ 12′ 9″ E). A field campaign was conducted in August 2015. The BFNP is covered in broadleaf, needle leaf (conifer) as well as mixed forest stands.

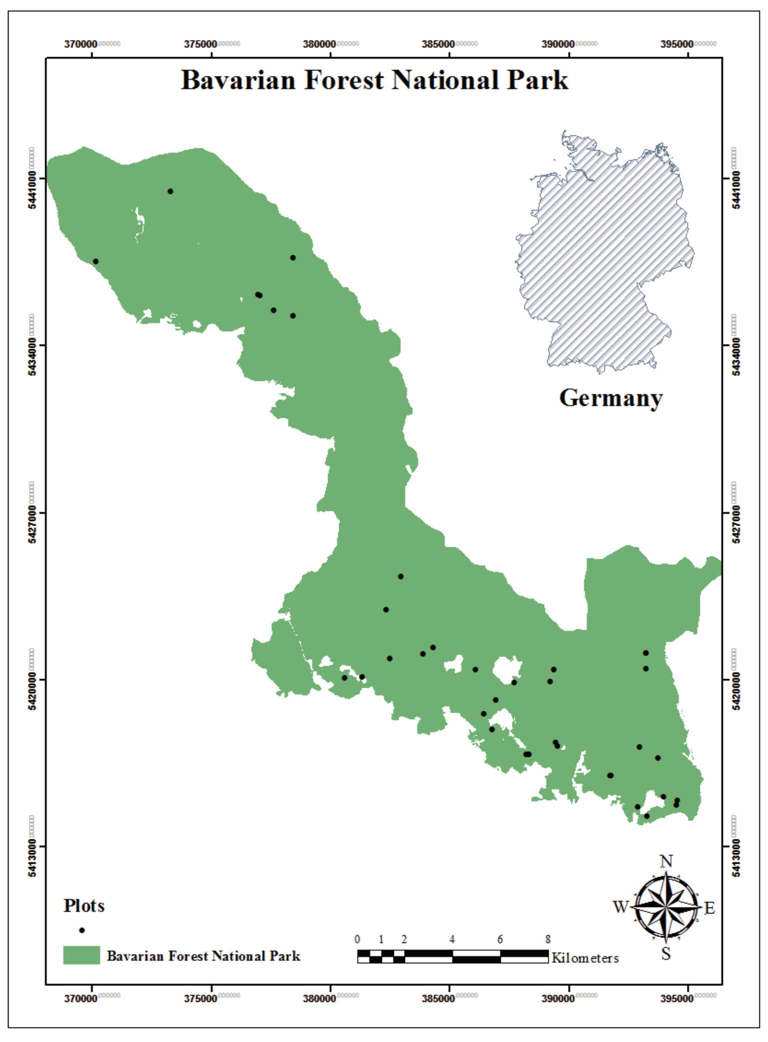

Figure 1. Location of the Bavarian Forest National Park, Germany and the distribution of the sample plots.

For each plot, the plants species were determined, and the proportion of vegetation cover (P_v) and LAI, representing the structural forest parameters were computed. A plant canopy analyser (LAI-2200, LICOR Inc., Lincoln, NE, USA) was used for measuring LAI in the field. The P_v of each plot was computed using five upward-pointing digital hemispherical photographs (DHP). The images were acquired using a Canon EOS 5D, equipped with a fish-eye lens (Sigma 8 mm F3.5 EX DF), levelled on a tripod at approximately breast height. The arithmetic mean of P_v estimated from the five images was then considered as the P_v of each plot.

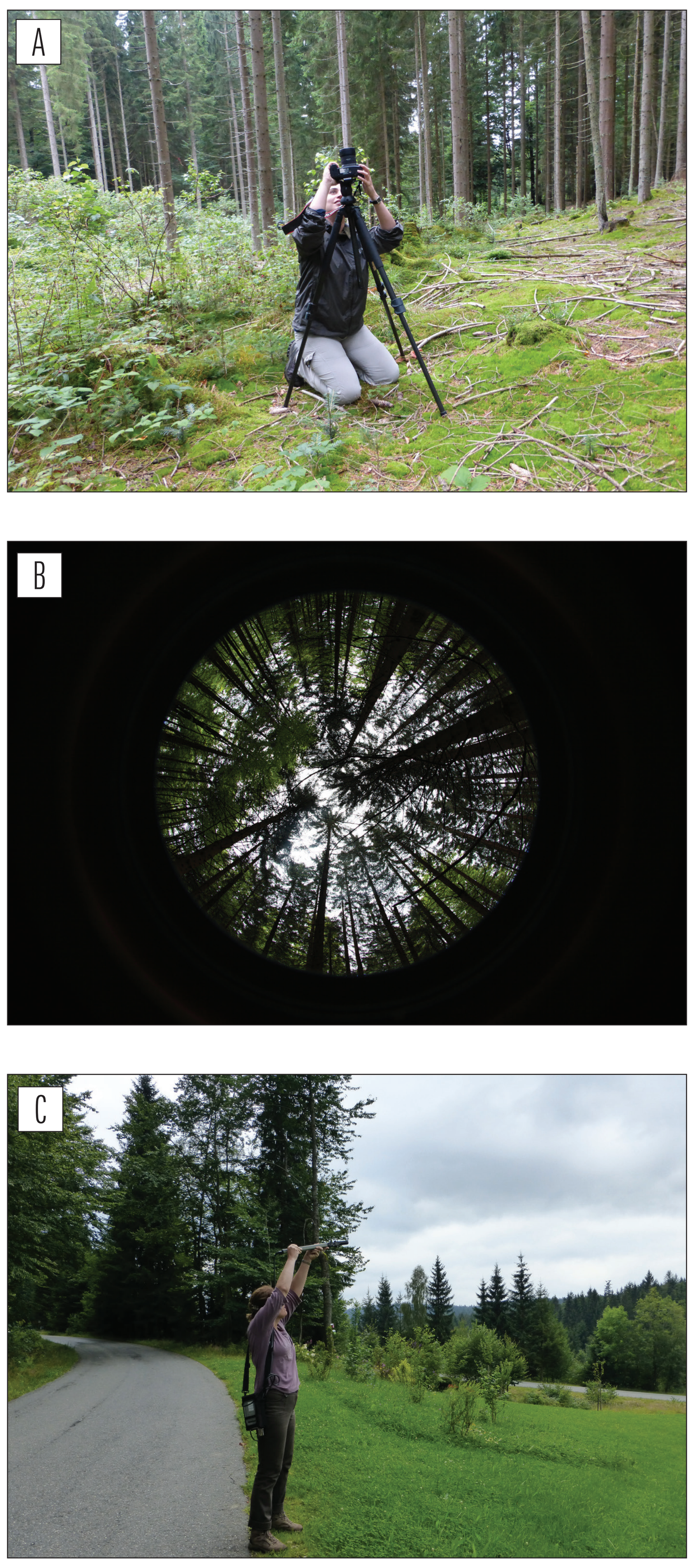

Figure 2. The filed campaign was conducted in the Bavarian Forest National Park (a), digital hemispherical photographs acquired during the field campaigns in 2015 (b), and a plant canopy analyser was used to measure leaf area index (c).

• Satellite data and processing

The Landsat-8 data were acquired on 9 August 2015 for the study area. The normalised difference vegetation index threshold method ($NDVI^{THM}$) was applied as a practical method to compute LSE. The LSE can be computed through the relationship between the NDVI and the vegetation and soil emissivity as follows [50, 52]:

$$LSE=\begin{cases} a\lambda + b\lambda\,\rho_{red} & NDVI<0.2 \\ \varepsilon_{v\lambda} + d_{\varepsilon} & NDVI\geq 0.5 \\ \varepsilon_{v\lambda}P_V + \varepsilon_{S\lambda}\times(1-P_V) + d_{\varepsilon} & 0.2\leq NDVI\leq 0.5 \end{cases} \quad (1)$$

where $a\lambda$ and $b\lambda$ are channel-dependent regression coefficients. ρred is reflectivity values in the red region. $\varepsilon_{v\lambda}$ and $\varepsilon_{s\lambda}$ are TIR band emissivity values for vegetation and bare soil, respectively. Both, $\varepsilon_{v\lambda}$ and $\varepsilon_{s\lambda}$ can be measured directly in the field or downloaded from emissivity spectral libraries or databases. In this study, $\varepsilon_{v\lambda}$ and $\varepsilon_{s\lambda}$ were extracted from the MODIS University of California- Santa Barbara (USA) (Wan and Dozier 1996). While P_v denotes the proportion of vegetation cover, $d\varepsilon$ stands for the cavity effect.

Regarding flat surfaces, $d\varepsilon$ is inconsequential; however, for diverse and rough surfaces such as a forest ecosystem, $d\varepsilon$ can gain a value of 2% (Sobrino 1989; Sobrino et al. 1990). In addition, $d\varepsilon$ can be calculated by applying the following equation:

$$d_{\varepsilon}=(1-\varepsilon_s)(1-p_v)F\varepsilon_v \quad (2)$$

where F is a shape factor, the mean value of which, assuming different geometrical distributions, is 0.55 (Sobrino et al. 1990; Sobrino et al. 2004).

• Estimation of leaf area index

In this study, a number of vegetation indices, which have been widely applied in the literature were used to estimate LAI using VNIR/SWIR data. Furthermore, LSE was integrated with the reflectance data as the input layers to examine the LAI retrieval accuracy using the artificial neural network as a machine learning approach.

❖ Results

LAI was predicted with modest accuracy using vegetation indices. However, when the reflectance from VNIR/SWIR data and LSE calculated from TIR data were integrated, the prediction accuracy of LAI increased significantly (R^2_{CV} = 0.81, $RMSE_{CV}$ = 0.75, m^2m^{-2}).

Table 1. The coefficients of determination (R^2) and cross-validation procedure among different indices calculated using reflectance over VNIR/SWIR domain and leaf area index.

Vegetation index	Abbreviation	R^2	Cross- validation procedure	
			R^2_{CV}	$RMSE_{CV}$
Difference Vegetation Index	SD	0.165	0.100	1.413
Ratio vegetation index	SR	0.373	0.308	1.230
Renormalised Difference Index	RDI	0.234	0.166	1.357
Modified Simple Ratio	MSR	0.292	0.227	1.305
Normalised Difference Vegetation Index	NDVI	0.313	0.321	1.288

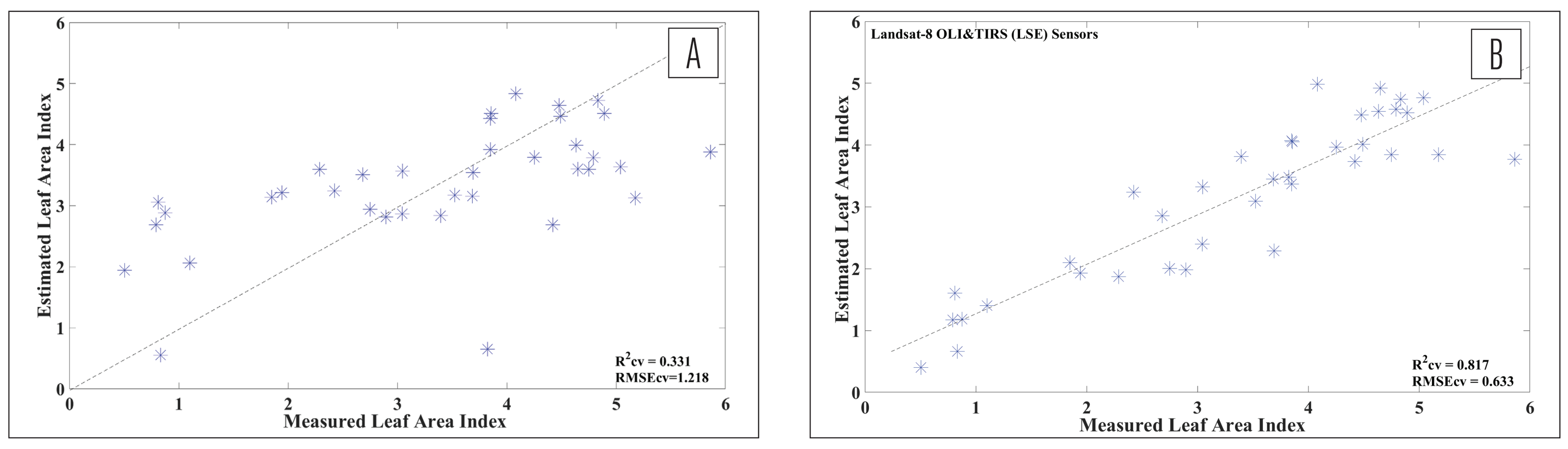

Figure 3. Scatterplot of estimated versus measured lead area index using modified vegetation index (a), and reflectance and land surface emissivity applying artificial neural network (b).

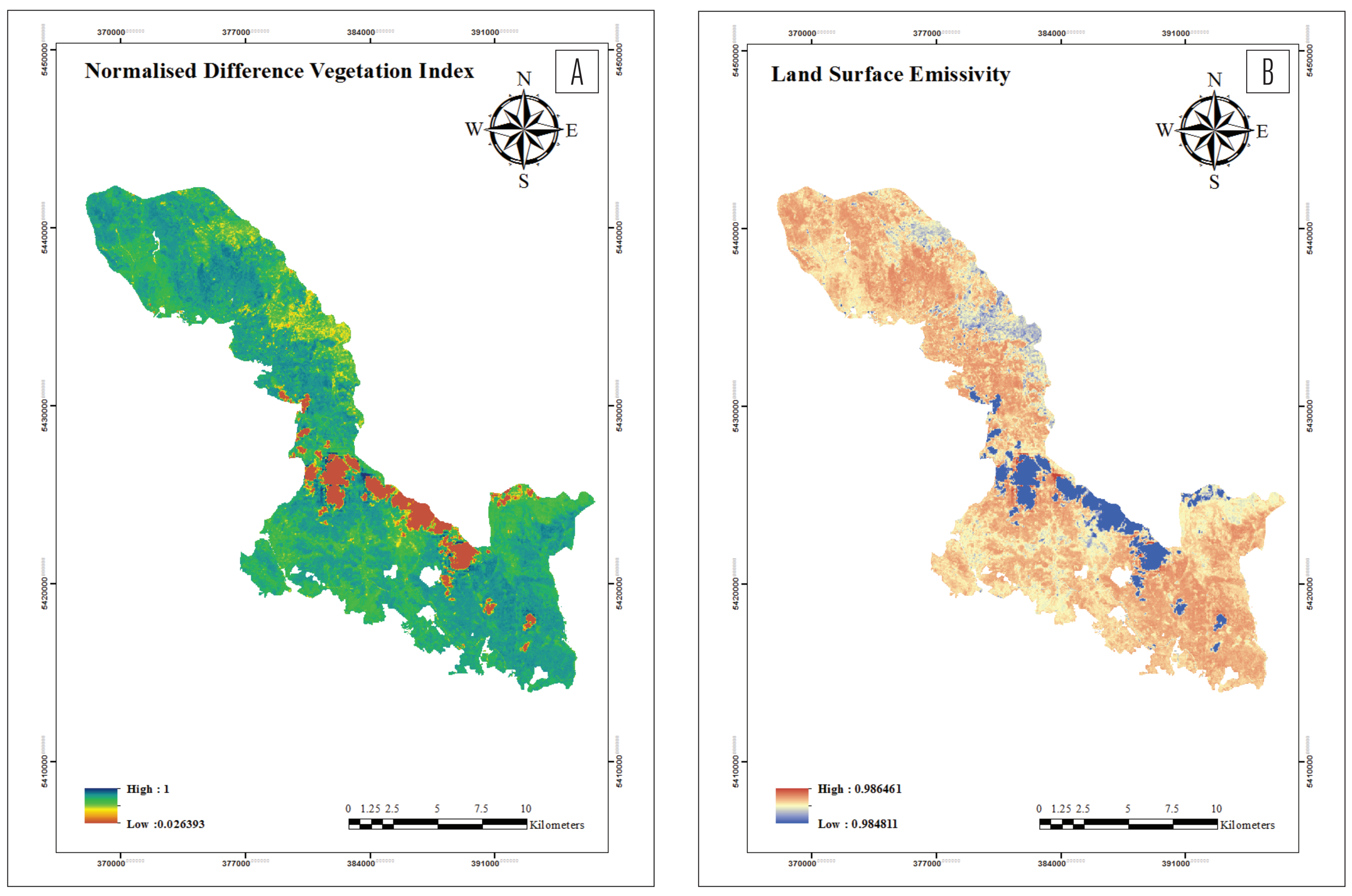

Figure 4. Normalised difference vegetation index (a), and Land surface emissivity (b) maps derived from the Landsat 8 imagery acquired on 9 August 2015 over the Bavarian Forest National Park.

❖ Conclusion

- Our results demonstrate that the combination of LSE and VNIR/SWIR satellite data can lead to higher retrieval accuracy for LAI.
- This finding has implication for retrieval of other vegetation parameters through the integration of TIR and VNIR/SWIR satellite data as well as regional mapping of LAI when coupled with a canopy radiative transfer model.

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