© EARSeL and Warsaw University, Warsaw 2005. *Proceedings of 4th EARSeL Workshop on Imaging Spectroscopy. New quality in environmental studies.*
Zagajewski B., Sobczak M., Wrzesień M., (eds)

ESTIMATING CONIFER FOREST LAI WITH HYMAP DATA USING A REFLECTANCE MODEL AND ARTIFICIAL NEURAL NETS

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ABSTRACT

The potential of canopy reflectance modelling to retrieve structural variables in managed Norway spruce stands was investigated using the invertible forest reflectance model INFORM. INFORM was derived by coupling FLIM, SAIL and LIBERTY models, and was inverted with hyperspectral airborne HyMap data using a neural network approach. A relatively simple three layer feed-forward backpropagation neural network with two input neurons, one neuron in the hidden layer and three output neurons was employed. Leaf area index (LAI) field measurements from 39 forest stands were used to validate the LAI estimates produced from HyMap reflectances. Using two HyMap wavebands at 837 nm and 1148 nm the obtained accuracy of LAI amounts to an rmse of 0.58 (relative rmse 18 % of mean). In contrast to approaches based on empirical relations between a spectral vegetation index and the biophysical variable of interest, the inversion approach is applicable to various sensor types and site conditions.

1 INTRODUCTION

Estimation of forest structural variables from remotely sensed data can be generally achieved by empirical or physical approaches. Empirical models relate a measure of reflectance (e.g., vegetation index, VI) to the variable of interest (e.g., canopy LAI) through a regression equation. The main drawbacks of such empirical models are that i) other variables influencing the radiation regime are not considered within the model, ii) that a relationship between a VI and the canopy variable of interest has to be developed for each field site using costly fieldwork data and iii) that effects of shadowing and multiple scattering are not considered (Asner et al., 2003).

These limitations are generally overcome by physically based approaches. In the forward mode, a radiative transfer model computes the spectral reflectance for a certain set of leaf and canopy parameters. Forward modelling provides an efficient way to investigate the effects of forest canopy variables on reflectance signatures and may improve the understanding of how the canopy structure and biochemical composition influences the radiation field (e.g., Bacour et al. 2002; Schlerf & Atzberger, 2002; Rautiainen et al., 2004). For the retrieval of canopy variables from measured signals it is necessary to invert the model. A successful inversion of a reflectance model requires three factors: a good model, an appropriate inversion procedure, and a set of calibrated reflectances (Jacquemoud et al., 2000).

Traditional inversion of reflectance models employs an optimisation technique to estimate the model parameters by minimising a merit function (Goel, 1988). An iterative process is necessary to find the optimal estimates of these parameters. The main drawbacks of this method are i) difficulty in achieving globally optimal and stable results, ii) difficulty in retrieving more than 2 parameters simultaneously (Gong et al. 1999), and iii) computational inefficiencies that prohibit an operational application on a per-pixel basis for regional or global studies (Kimes et al., 2002). Recently, Artificial Neural Networks (ANN) have been employed for reflectance model inversion (Gong et al., 1999; Udelhoven et al., 2000; Kimes et al., 2002) to overcome the above mentioned limitations. However, neural network approaches for the inversion of forest reflectance models using satellite or airborne remote sensing data that include a validation with ground truth data, are non-existing or rare. This was attempted in the present study.

2 METHODS

The Idarwald forest (49°45'N, 7°10'E), located in south-western Germany, covers an area of about 7,500 ha and is dominated by managed stands of *Picea abies* (Norway spruce). In 1999, 39 relatively homogenous spruce stands were identified at the study area and within these stands quadratic plots of 30 m side length were established. The central location of each ground plot was determined with an accuracy of about ±5 m using a differential GPS device. At each plot, measurements of forest biophysical variables were carried out during summer and autumn of 2000. Measured biophysical variables included leaf area index (LAI), stem density (SD), canopy closure (CO), stand height (H) and crown diameter (CD).

LAI was estimated using a Li-Cor LAI-2000 Plant Canopy Analyser (PCA). The instrument estimates effective LAI using measurements of diffuse solar radiation above and below the forest canopy. The LAI-2000 was only operated under overcast sky conditions between daytimes with a 270-degree view restrictor on the sensor. Below canopy measurements were taken at 10 regularly spaced points within each plot, from which the average was calculated. Above canopy measurements were taken in a nearby open field before entering the plots and attention was paid to measure during stable sky conditions. It was assumed that the underestimation of LAI due to clumping effects was somehow compensated by the overestimation of LAI through woody structures (Fournier et al., 2003). Consequently, the retrieved LAI-2000 PCA measurements represent an effective plant area index instead of the real leaf area index. In the following sections these measurements are abbreviated as LAI. Stem density (SD) was obtained by counting the number of trees in a plot. Crown closure (CO) was visually estimated in steps of 5 percent. Stand height (H) was calculated from the mean height of three dominant trees that were randomly selected within each plot. The height of each tree (from the ground to the top) was estimated from angular measurements. As forest stands at Idarwald consist of trees of the same age, dominant trees within a stand have similar heights and the selection of three trees to represent stand height was considered to be appropriate.

The HyMap sensor was flown over the Idarwald test site on 17th July 1999 at an average flying height of 1980 m above ground level. The ground resolution was about 5 m with a full scene covering approximately 3 km x 10 km. Radiometric and geometric pre-processing steps applied to the HyMap data have been described in detail in Schlerf et al. (2005). Radiometric pre-processing consisted of an across track illumination correction to remove the view angle effect (Kennedy et al., 1997), and a combined sensor calibration and correction of atmospheric and illumination effects (Hill & Mehl, 2003).

The Invertible Forest Reflectance Model INFORM (Atzberger, 2000) simulates the bi-directional reflectance of forest stands between 400 and 2500 nm. INFORM is essentially an innovative combination of FLIM (Rosema et al., 1992), SAIL (Verhoef, 1984), and PROSPECT (Jacquemoud & Baret, 1990) or LIBERTY (Dawson et al., 1998). In INFORM, LAI is a single tree LAI (LAI_s). Canopy LAI (LAI_c) can be expressed as the product of LAI_s and crown closure (CO). CO is calculated as a function of stem density (SD) and crown diameter (CD). To model forest reflectance of a certain LAI_c, the values of LAI_s, SD, and CD and also the tree height (H) have to be defined. Site specific information was used to parameterise the model correctly and to model corresponding forest reflectance spectra. The remaining external, leaf and canopy parameters were set to default values as defined by Atzberger (2000) and were kept constant for all simulations.

The general procedure for the estimation of forest attributes from HyMap data through inversion of the reflectance model consisted of four major steps: (a) forward modelling to generate synthetic canopy spectra, (b) training of the neural network using the modelled data, (c) application of the trained ANN to measured HyMap spectra to estimate forest canopy variables and for eventually modifiying the network architecture, and (d) the application of the final ANN to the image for generation of bio-physical parameter maps. Training of the network was done by presenting modelled spectra and corresponding canopy variables to the ANN. During the training process, the values of the weights and biases in the network are iteratively adjusted in such a way that the error between the network outputs and the target outputs (the canopy variables) is minimised. Before the modelled canopy variables and spectra could be presented as training data to the ANN, certain bands were selected and the data was normalised (z-transformation). Statistical parameters of the z-transformation (mean and standard deviation) were later used to normalise the measured data in exactly the same way.

For training the resilient backpropagation algorithm was applied. The purpose of this training algorithm is to eliminate harmful effects of the magnitudes of the partial derivatives that may be caused when using steepest descent to train a multilayer network with sigmoid functions. Only the sign of the derivative is used to determine the direction of the weight changes; the magnitude of the derivative has no effect on the weight changes (Demuth & Beale, 2003). One of the main problems that typically occur during ANN training is overfitting. This phenomenon describes the situation that the error on the training data is driven to a very small value, but when new data is presented to the network the error is large (Demuth & Beale, 2003). This lack of generalisation can be avoided by using a network that is just large enough to provide an adequate fit. The complexity of a network is mainly determined by the number of neurons in the hidden layer. To find the appropriate dimension of the hidden layer, the performance of the algorithm was systematically investigated with the number of neurons in the hidden layer varying between 1 and 10; it turned out that one neuron in the hidden layer was sufficient to approximate the function between input and output vectors. To further improve generalisation of the network the early stopping technique (Demuth & Beale, 2003) was applied. The patterns generated with INFORM were divided into two subsets. 2500 datasets were used for training, and 2500 were used as a test dataset to prevent overfitting. The training set was used for computing the gradient and updating the weights and biases. The error on the test set was monitored during the training process. During the initial training phase, both, training and test set error decreased. When the network began to overfit the data, the test set error started to rise. At this point the training was stopped and the actual weights at the minimum of the test error were returned. These weights and biases were then used to estimate the independent variables of the validation dataset.

The measured HyMap spectra and the field-measured canopy variables were used as validation dataset. All assessments concerning the performance of the ANN are based on the results obtained with the validation set. The structure of the ultimately used ANN was relatively simple (Figure 1). It had two input neurons (equal to the number of used wavebands), one neuron in the hidden layer, and three output neurons (one for each variable to be estimated). A three layer feed-forward backpropagation network with a tan-sigmoidal transfer function in the hidden layer and a linear transfer function in the output layer was employed.

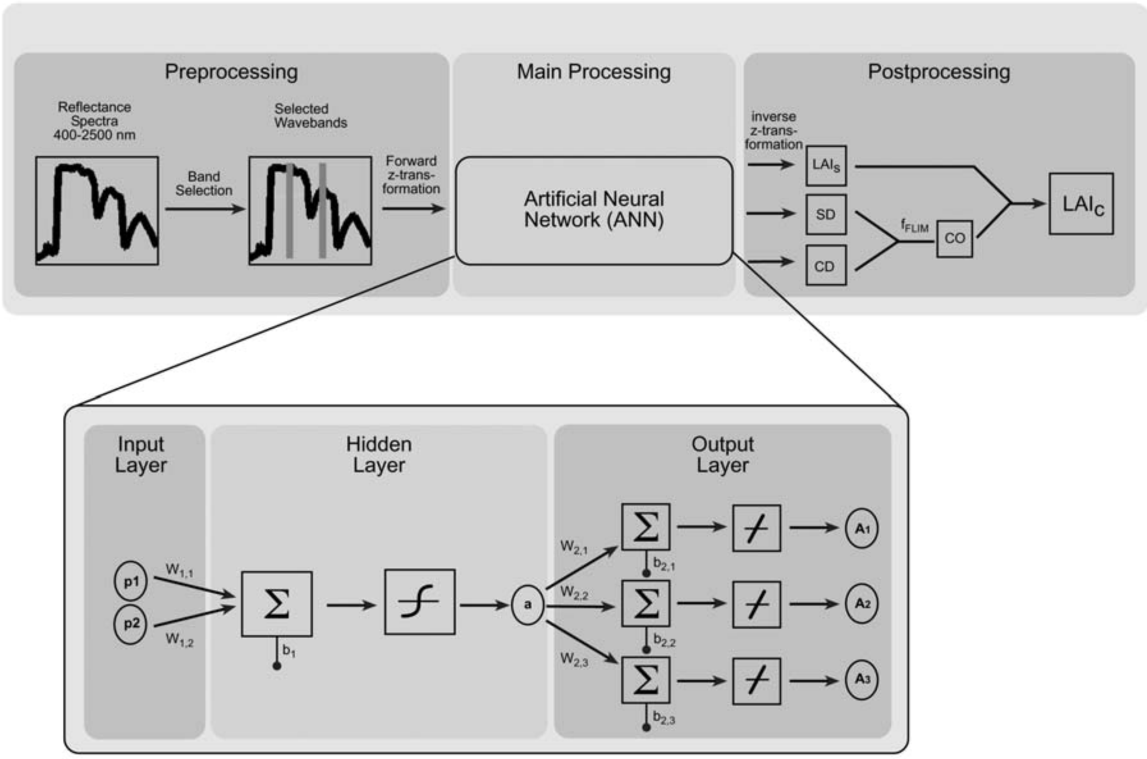

Figure 1: Structure of the Artificial Neural Network used to invert the INFOR model. See text for details.

3 RESULTS

The validation data (i.e. the HyMap spectra and the biophysical data) was preprocessed in exactly the same way as the training set. That means, the same wavebands were selected from the measured HyMap spectra. Both reflectances and biophysical data were normalised with the same statistical parameters that had been previously used for the z-transformation of the training data. After the HyMap spectra were sent through the network, the resulting network outputs were subjected to an inverse z-transformation and from the estimated values of LAIs, SD, and CD, estimated values of CO and LAIc were computed. The coefficient of determination and the root mean squared error between estimated and field-measured forest canopy variables were calculated. Both parameters served as a measure of accuracy of the model inversion.

Using two HyMap wavebands at 837 nm and 1148 nm, model estimated and ground LAI show relatively good agreement as indicated by the close position of most data points along the 1:1 line (Figure 2). Low values of ground LAI are slightly overestimated whereas relatively large values of ground LAI are somewhat underestimated. The obtained accuracy of the LAI map amounts to an rmse of 0.58 (relative rmse 18 % of mean) with a coefficient of determination (R^2) of 0.73. As expected, crown closure and stem density behave similar with LAI with respect to the 1:1 line.

CONCLUSIONS

Our results further show that a combination of FLIM, SAIL and LIBERTY models can be inverted with a neural network approach to give estimates of important structural forest characteristics. Relatively simple network architecture with just one neuron in the hidden layer proofed to be suitable to solve the inversion problem.

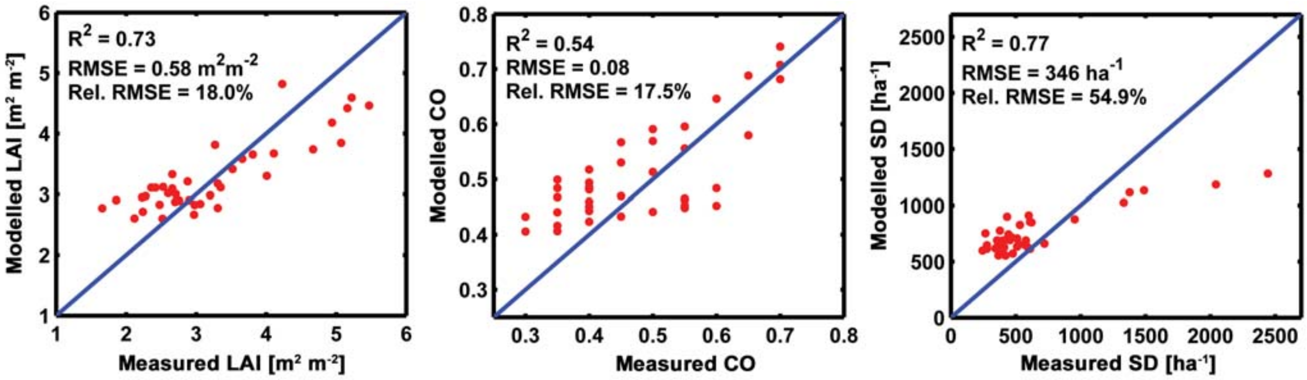

Figure 2: Modelled against measured forest LAI (n = 39).

ACKNOWLEDGEMENTS

This research was financially supported by the German Research Community (DFG). Provision of the HyMap imaging spectrometer data by Andreas Müller (German Aerospace Center, DLR) is greatly acknowledged. The authors are particularly grateful to Joachim Hill for radiometrically correcting the HyMap data using software package AtCPro 3.01. The aid of Samuel Bärisch and Henning Buddenbaum during field work is highly acknowledged. The authors thank Terry Dawson for providing the LIBERTY model.

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