Validation of Neural Net techniques to estimate canopy biophysical variables from remote sensing data

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Abstract

A Bidirectional Reflectance Distribution Function ($BRDF$) catalog of different crops (mainly wheat, alfalfa, sunflower and maize) has been acquired thanks to Alpilles/ReSeDA campaign, over the whole crop cycles in 1997. This was achieved using the airborne *POLDER* sensor. The aim of this study is to test the ability of neural network techniques to accurately estimate canopy biophysical variables from reflectance data. The biophysical variables of interest considered are cover fraction and leaf area index. A well known and validated canopy radiative transfer model ($SAIL$) is first used to simulate two BRDF databases: (1) a learning data set allow to train the neural networks; (2) the second data set allow a first validation of this technique. In a second time, we use ReSeDA *POLDER* products and apply the calibrated neural networks to derive biophysical variables estimates. These estimates are then compared to *in situ* measurements for the 16 acquisition dates and different fields and crops. We also compare $NNet$ $NNet$ performances versus a NDVI-based technique.

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1 Introduction

Protecting our environment and understanding the impact of the human activity on the processes that occur at the Earth surface is one of the main concern of the XXIth century. The characterization of the continental biosphere in terms of canopy biophysical variables is thus of prime interest in many applications that allow global change understanding. Remote sensing appears to be a very powerful tool to get quantitative, temporal and spatial information about those variables. Large swath sensors with relatively high temporal repetitivity such as *POLDER, NOAA/AVHRRR, VEGETATION, MODIS, MISR*, ..., allow a frequent coverage of the Earth surface. Concurrently, different methods to estimate canopy biophysical variables from reflectance data were elaborated:

- Vegetation Indices (VI) approach: VI are band combinations of reflectance values. The most simple one is the Normalized Difference Vegetation Index $NDVI$ (Rouse et al., 1974) which is based on the contrast between the soil and vegetation reflectance in the red and near-infrared domains. Many authors have developed empirical relationships between VIs and canopy biophysical variables. This methods are interesting since they are very simple but the accuracy of biophysical variable estimation may be quite low. Moreover, VIs are usually sensitive to the soil background, canopy chlorophyll content, or to the orientation and spatial distribution of the leaves in the canopy (Asrar et al., 1984; Sellers et al., 1994; Carlson and Ripley, 1997; Gobron et al., 1999).

- Physical modeling approach: it is based on the inversion of canopy reflectance models that describe the radiative transfer in the canopy as a function of biophysical variables which characterize the canopy architecture and the optical properties of vegetation elements and soil. Model inversion is usually more accurate than VI but it is based on iterative and time consuming optimization processes that are sensitive to the initial guess of the solution (Pinty and Verstraete, 1991; Hall et al., 1995; Bicheron and Leroy, 1999).

- Hybrid approach: it is based on the elaboration of a learning data base that is the most representative as possible of what the sensor should observe. In this data base, each canopy is characterized by biophysical variables corresponding to reflectance values. Look-Up-Tables (LUT) consists in computing the distance between a set of measured reflectances and reflectance values of each canopy in the LUT. The estimated canopy variables are those of the LUT element for which this distance is minimum (Knyazikhin et al., 1998). Neural Network ($NNet$) can be considered as a "black box" that fit a relationship between reflectance values and canopy biophysical variables (Smith, 1993; Jin and Liu, 1997; Kimes et al., 1997; Abuelgasim et al., 1998). The calibration is performed on the learning data set. The main difference is that $LUTs$ focus on the minimal distance between reflectances although $NNets$ minimize the distance between canopy biophysical variables. Once the learning phase is achieved, hybrid approaches are accurate, fast and require low computer resources.

This study is dedicated to the development and the validation of a vegetation monitoring algorithm from satellite data. The estimation of canopy biophysical variables from bidirectional reflectance data is performed using $NNets$ techniques. We consider leaf area index (LAI) and nadir gap fraction (P_o) that are of prime interest for canopy functioning or evapotranspiration modeling (Yang et al., 1999). A synthetic database is generated using well-known radiative transfer models to allow the calibration of the $NNets$. As neural networks require a constant number of normalized inputs, reflectance data are first pre-processed. Finally, performances are compared to the $NDVI$ based technique for the estimation of the nadir gap fraction (P_o) and Leaf Area Index (LAI). This is performed both on simulated and experimental data sets. The impact of spatial resolution is also investigated using the experimental data from the Alpilles ReSeDA campaign.

2 Generation of the synthetic learning data base

The learning data base, composed of biophysical variables and corresponding bidirectional reflectance values, is used for the calibration of $NNets$. It is therefore necessary to get a wide range of situations including a variety of canopies. Since no such a data set exists, we generate it using well-known radiative transfer models. The learning data base is better representative of the reality that the radiative transfer model is accurate and that the range of variation of its inputs is realistic.

2.1 Model used

Numerous radiative transfer models are developed in the literature, from the most simple and empirical ones such as linear BRDF models (Wanner et al., 1995) to the most complex and physically based ones such as radiosity (Chelle and Andrieu, 1998) or ray-tracing models. Considering that we perform 1500 simulations, we have to make a compromise between the model accuracy, time consuming of the simulations and the number and physical signification of the model input variables. We thus use the $SAIL$ model (Verhoef, 1984, 1985) that has been validated by many authors on various canopies (Goel and Thompson, 1984; Badwahr et al., 1985; España, 1997). This model was modified by Andrieu et al. (1997) to include the hot spot feature (Kuusk, 1991). $SAIL$ requires the leaf (resp. soil) optical properties that are simulated with the $PROSPECT$ model (Jacquemoud and Baret, 1990), (resp. $SOILSPECT$ model (Jacquemoud et al., 1992). Simulations are performed in airborne $POLDER$ bands, center at 550nm, 670nm and 864nm. As we assume that reflectance data are atmosphere corrected, the blue band is not considered since it is the most affected by the atmospheric effects.

2.2 Range of input variables

Table 1 describes the variation of the input variables used to generate the learning data base. The range of leaf optical properties is given by the $LOPEX$ data set (Hosgood et al., 1995). The variation of $SOILSPECT$ input variables corresponds to that of Jacquemoud et al. (1992). Structure parameters are uniformly distributed between realistic values. As the algorithm should be adapted for any sensor, we consider that the acquisition could be performed at any date, for any latitude. To determine observation condition, the orbitography of the *VEGETATION* sensor over the 26 days of its orbital cycle is taken as an example.

2.3 Biophysical variables of interest

As our aim is the estimation of biophysical variables from remote sensing data, we only focus on such variables that influence strongly or are derived from the radiative transfer process. We thus consider one primary variable, LAI, that is a $SAIL$ input, and a secondary variable P_o that corresponds to the complementary to one of the vegetation cover fraction and is computed by the $SAIL$ model.

At the end of the simulations, we obtain the top of canopy bidirectional reflectance data and the corresponding biophysical variables of 1500 homogeneous canopies various in structural and optical properties and under different illumination conditions. The data set is divided in two independent parts: the first one is the learning data set used to fit relationships between biophysical variables and reflectance data, and the second one is the test data set which allows to evaluate the retrieval performances of biophysical variables.

3 Calibration of $NNets$ and $NDVI$ techniques

Two methods were developed for nadir gap fraction and leaf area index estimation from a set of bidirectional reflectance data. The first one is empirical and based on the computation of $NDVI$ and on the existing relationships between $LAI/NDVI$ and $P_o/NDVI$. The second one consists in using $NNets$ to directly relate reflectance data to biophysical variables. As the number and direction of large swath sensor observations depends on latitude and cloud occurrence, bidirectional reflectance data are first pre-processed by using a linear $BRDF$ model. The performances of $NNets$ and $NDVI$ are compared using the Root Mean Square Error ($RMSE$) and the T statistics that measures the scattering around the (1:1) line. When T is close to 1.0, the fitting is very good.

$$RMSE = \sqrt{\frac{1}{n}\sum_n x - \hat{x}^2} \quad (1)$$

$$T = 1 - \frac{\sum_n x - \hat{x}^2}{\sum_n x - \bar{x}^2} \quad (2)$$

where x (resp. $\hat{x}$) is the measured (resp. estimated) variables, n is the number of data and $\bar{x}$ the average of x over the n samples.

3.1 Pre-processing the bidirectional reflectance data

A linear $BRDF$ model is used to normalize the $BRDF$ acquired by the sensor. This is required both for the use of $NDVI$ (to be able to compare the same quantity from one pixel to another or from one date to another) and $NNets$ that require a constant number of inputs. Among the numerous $BRDF$ models existing in the literature (cf review of Wanner et al. (1995)), the $MRPV$ model (Engelsen et al., 1996) appears to be one of the most performant (Weiss et al., 2000). The choice of this model is driven by the following arguments:

- Linearity : it resumes the fitting over the observed BRDF samples to a matrix pseudo-inversion which significantly reduces the computation time;
- Limited number of parameters : depending on the latitude and cloudiness, only few directional data are available;
- The model should accurately fit the reflectance data to keep the directional information;
- The parameters should remain quite constant whether the inversion is done over the whole reflectance data or only on a restricted amount of these data;

The $MRPV$ model is semi-linear and requires three parameters α_i:

$$\ln \frac{\rho(\theta_v, \theta_s, \phi)}{H} = \alpha_1 + \alpha_2 \ln \cos\theta_s \cos\theta_v (\cos\theta_s + \cos\theta_v) + \alpha_3 \cos\xi \tag{3}$$

where H is the hot spot function which depends on view (θ_v) and solar (θ_s) zenith angles and the relative azimuth angle (ϕ), and ξ is the phase angle. Besides $MRPV$ parameters, we also compute the nadir reflectance (ρ_0) that is usually used as a normalized parameter. The hemispherical reflectance (ρ_h) is also very useful to get an estimate of the canopy albedo. We compute it by integration of the bidirectional reflectance in a Gaussian quadrature.

The accuracy of the model fitting is first tested on the simulated data set (Fig. 1): the model is inverted on a random selection of data (20%, 50% 80%, and 100%) to take into account cloud occurrence. It is then run in the forward direction to retrieve all the bidirectional reflectance data. Results are globally satisfactory with a relative $RMSE$ ($RMSE$ divided by the amplitude of the reflectance) between estimated and measured reflectance lower than 0.03%. The $RMSE$ increases with the percentage of cloud since the number of data used for the fitting decreases. The model presents thus good extrapolation capacities to fit the bidirectional reflectance data.

As stated earlier, the parameters should remain quite constant whether the inversion is performed over the whole reflectance data or only on a restricted amount of these data. Fig. 2 shows the relative $RMSE$ between estimated $MRPV$ parameters by inverting the model over all or a selection of directions. The nadir reflectance keeps very stable whether 100% or 20% of the observation directions are used for the fitting. The same behavior is observed for both $MRPV$ parameters and hemispherical reflectance, with higher $RMSE$, except for α_2 that is not stable.

3.2 $NDVI$ based method

Among the numerous vegetation indices developed (Baret and Guyot, 1991), the $NDVI$ is one of the most used in many applications. It is based on the contrast between the soil and the vegetation behavior in the red and near infrared domains. Following the results of § 3.1, we consider the nadir $NDVI$.

$$NDVI = \frac{\rho_0(865nm) - \rho_0(670nm)}{\rho_0(865nm) + \rho_0(670nm)} \tag{4}$$

Nadir $NDVI$ and P_0 are both related to LAI by exponential laws (Asrar et al., 1984; Nilson, 1971), which allow the derivation of P_0 as a function of $NDVI$.

$$P_0 = \left(\frac{NDVI - NDVI_\infty}{NDVI_s - NDVI_\infty}\right)^{K_{P_0}} \tag{5}$$

$$LAI = -\frac{1}{K_{LAI}} \ln \frac{NDVI - NDVI_\infty}{NDVI_s - NDVI_\infty} \tag{6}$$

where

- $NDVI_\infty$ is the asymptotic value of nadir $NDVI$ when LAI tends to ∞ (practically, LAI=8);
- $NDVI_s$ is the bare soil $NDVI$ value;
- K_{LAI} and K_{P_0} are extinction coefficients.

To evaluate those four parameters, we use the simplex method (Nelder and Mead, 1987) to minimize a cost function. This function is defined as the $RMSE$ between estimated variables from eq 5 and 6 and their actual value. The relationship is fitted on the learning data set ($NDVI_\infty$=0.96, $NDVI_s$=0.13, K_{LAI} = 0.67 and K_{P_0}=0.72) and validated on the test data set (Tab. 2). A large scattering around the (1:1) line (low T values) is observed due to the sensitivity of $NDVI$ to the canopy geometry, soil background, and sun geometry.

3.3 $NNets$ based method

The main advantage of $NNets$ is that, although the learning stage takes a long time due to optimization process, it provides instantaneously the solution when run in the forward direction. Neural networks are characterized by the type of neurons used (with a weight, a bias and a transfer function), the way that they are organized (number of layers and number of neurons per layer), and the learning rule. In this study, we use the back-propagation algorithm to calibrate the neural networks (Rummelhart et al., 1986). 50 $NNets$, corresponding to 50 different initializations of weights and biases are trained in parallel to control the stability of the solution. The estimated variable is computed as the median value over the 50 $NNets$. To increase $NNets$ performances, we normalize the input/output parameters with respect to their minimum and maximum values over the learning data set. This allows reaching the solution faster. Over-fitting on the calibration data set is avoided by stopping the training when the $RMSE$ value between estimated and actual output variables decreases on the learning data set and increases on the over-fitting data set. The over-fitting data set is composed of Alpilles/ReSeDA data acquired on wheat (§ 4).

Nadir gap fraction estimation: considering that the relationship between P_0 and reflectance is quite simple (linear), and that nadir reflectance is very stable by $MRPV$ inversion, $NNet$ inputs are ρ_0 in the three $POLDER$ bands and the cosine of the solar zenith angle. We have a two hidden layer network, with respectively 4 logsigmoïd and one linear neurons. Increasing the number of neurons or layers leads to over-fitting. The networks converge after about 100 iterations and remain stable after.

Leaf area index estimation: considering that the relationship between LAI and reflectance is non linear, the hemispherical reflectance in the 3 wave bands are added to ρ_0 and the cosine of the solar zenith angle to get the $NNet$ inputs. We have a three hidden layers network, with respectively 4 logsigmoïd, 2 logsigmoïd and one linear neurons.

Results: Table 2 shows that $NNet$ performances are much better than $NDVI$, both for LAI and P_0. $RMSE$ is divided by 4 for P_0 and by 2 for LAI. The scattering around the (1:1) line is higher for LAI than for P_0 since there is a saturation of the reflectance for high $LAIs$. This feature is increased when considering $NDVI$ estimates.

4 Validation of $NNets$ and $NDVI$ techniques on the Alpilles/ReSeDA data set

The experimental site is an agricultural area (5kmx5km) located in the south of France (N43^{0}47, E4^{0}45). Measurements were performed from October 96 to November 97, on various crops (Prévot et al., 1998). Airborne reflectance measurements were achieved monthly using the $POLDER$ instrument. Five flight lines allowed the $BRDF$ acquisition. Spatial resolution was 20m. Images were corrected from instrumental, geometrical and atmospheric effects. Ground measurements of LAI were performed using a planimeter. To derive the nadir gap fraction from LAI data, we used relationships existing in the literature (Tab. 3).

4.1 Nadir gap fraction and leaf area index estimation

$NNets$ and $NDVI$ methods are applied for both LAI and P_0 estimation (Fig. 3, Tab. 4). We retrieve the results obtained on the synthetic data set with higher $RMSE$ values due to the residual noise observed on reflectance data. Performances are better for P_0 than for LAI. $NNets$ perform better than $NDVI$. The difference between the two methods for the estimation is however less important than for the synthetic data set: $RMSE$ divided by 1.6 for P_0 and by 1.1 for LAI. This is mainly due to the fact that there is only 12% of the measurements that corresponds to $LAIs$ higher than 2.5, for which the saturation effect is much higher with $NDVI$.

4.2 Impact of the spatial resolution for P_o and LAI estimation.

As we consider data provided by large swath satellite sensors, we have to study the impact of the spatial resolution on the retrieval of nadir gap fraction and leaf area index. A 1km by 1km square is thus extracted from the center of the $ReSeDA$ site. For this area, we compared the estimates, using two methods for the 16 flight dates:

1. The $NNet$ input variables are averaged over 50 $POLDER$ sub-pixels of the 1km^2 area. Corresponding LAI and P_0 values are computed;
2. We run $NNets$ to get LAI and P_0 for each $POLDER$ sub-pixels, and average those values on the whole 1km^2 area.

As there is an important part of bare soils, we observe only low LAI values (fig. 4). Results show that the nadir gap fraction estimation is not sensitive to the spatial resolution, since it is quite linearly related to the reflectance. Conversely, the LAI is much more sensitive to the spatial resolution and is underestimated with (1) as compared to (2). This leads to the conclusion that leaf area index is underestimated when using large swath sensors.

5 Conclusions

This study is dedicated to the estimation of canopy biophysical variables from bidirectional reflectance derived from large swath satellite data. This algorithm, based on neural networks, is built on a data set generated with radiative transfer models. As compared to the $NDVI$, it presents good performances of estimation on synthetic as well as on experimental data. Results show that nadir gap fraction is more accurately estimated than LAI due to the saturation of the signal for dense canopies. The estimation of LAI is also sensitive to the spatial resolution. The algorithm we developed can be extended for any large swath sensors. It also includes a way to normalize reflectance data. This study requires further validation on actual data, corresponding to a wide range of canopies, especially forest and sparse vegetation.

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Tables

Table 1. Range of radiative transfer model inputs. For Gaussian law (G), m and σ stand for the average and standard deviation values. U stands for uniform distribution law.

Model Inputs	Distribution Laws
Structure variables	
Leaf Area Index LAI	U, min=0, max=6
Average Leaf Angle	U, min=15^0, max=75^0
Hot Spot parameter	U, min=0.01, max=1
Leaf Optical Properties	
Chlorophyll ($\mu g.cm^{-2}$)	G, m=50, σ = 16
Water (cm^{-1})	G, m=0.01σ = 0.0024
Dry Matter ($g.cm^{-2}$)	G, m=50, σ = 0.0024
Mesophyll parameter	G, m=1.63, σ = 0.26
Soil Optical Properties	
Roughness	U, min=0, max=0.03
Phase Function	U, min=-1.8, max=1.8
Phase Function	U, min=0.05, max=1
Single Scattering Albedo	Jacquemoud et al. (1992)
Viewing Conditions	
Day of the year	U, min=1, max=365
Latitude	U, min=0, max=67^0

Table 2. $NDVI$ and $NNet$ performances on the synthetic test data set.

	$NDVI$		$NNet$	
	$RMSE$	T	$RMSE$	T
P_0	0.16	0.76	0.04	0.98
LAI	1.10	0.69	0.53	0.92

Table 3. Relationships used to derive nadir gap fraction from LAI planimeter measurements. For Alfalfa, no value was found in the literature.

Crop		Authors
Wheat	$\exp(-0.34LAI)$	Baret et al. (1993)
Maize	$\exp(-0.34LAI)$	España (1997)
Sunflower	$\exp(-0.6LAI)$	Shell et al. (1974)
Alfalfa	$\exp(-0.5LAI)$	

Table 4. $NDVI$ and $NNet$ performances on the Alpilles/ReSeDA data set.

	$NDVI$		$NNets$	
	$RMSE$	T	$RMSE$	T
P_0	0.13	0.75	0.08	0.9
LAI	0.49	0.79	0.44	0.82

Figure Captions

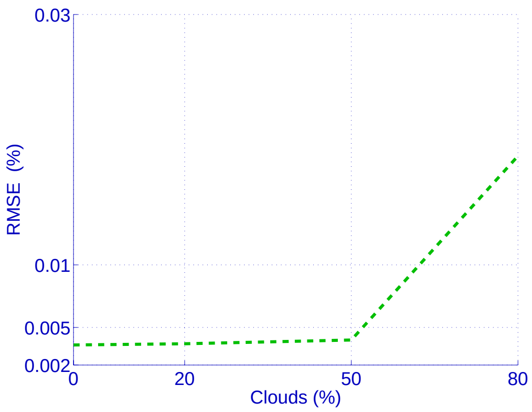
Fig. 1. Extrapolation capacities of the $MRPV$ model. The model inversion is first performed on a restricted amount of data. Bidirectional reflectance is then estimated in all directions of observation.

Fig. 2. Stability of $MRPV$ parameters (α_i), nadir reflectance (ρ_o) and hemispherical reflectance (ρ_h).

Fig. 3. Nadir gap fraction and leaf area index estimation using $NNets$ on the Alpilles/ ReSeDA data. (●:maize, ■:wheat, △: sunflower, ⋄:alfalfa)

Fig. 4. Testing the impact of spatial resolution of LAI and P_0 estimation for the 16 $POLDER$ acquisition dates. (1) Using the averaged reflectance over the 1km^2 pixel as input to $NNets$. (2) Using the averaged $NNet$ output.

Figures



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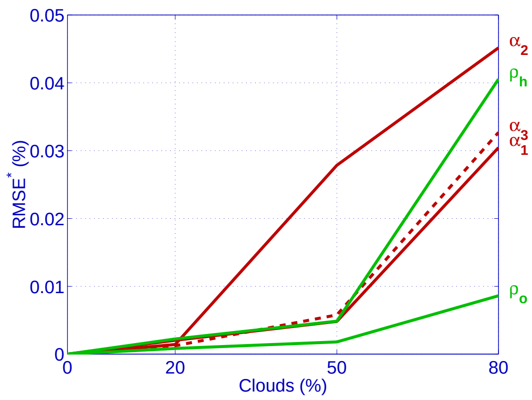

Fig. 2. Stability of $MRPV$ parameters (α_i), nadir reflectance (ρ_o) and hemi-spherical reflectance (ρ_h).

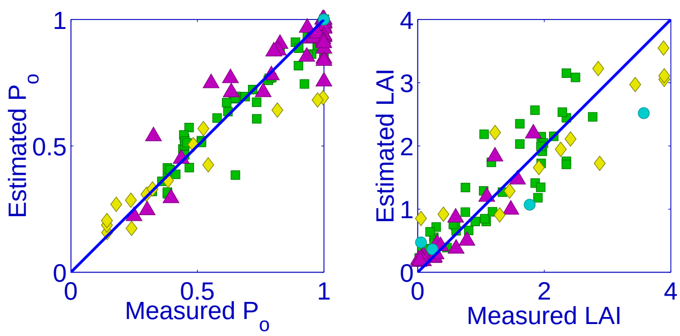

Fig. 3. Nadir gap fraction and leaf area index estimation using $NNets$ on the Alpilles/ ReSeDA data. (●:maize, ■:wheat, △: sunflower, ⋄:alfalfa)

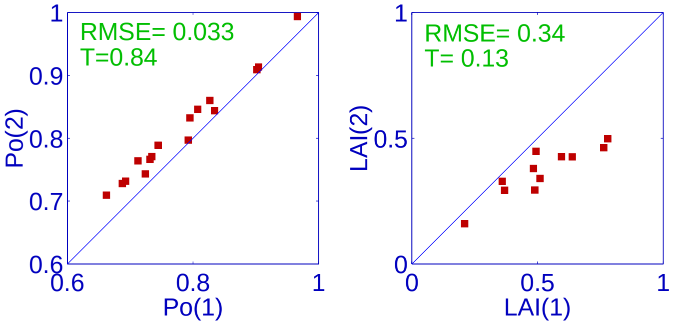

Fig. 4. Testing the impact of spatial resolution of LAI and P_0 estimation for the 16 $POLDER$ acquisition dates. (1) Using the averaged reflectance over the 1km^2 pixel as input to $NNets$. (2) Using the averaged $NNet$ output.