# Prototyping of physically based methods to retrieve leaf area index and canopy water content from satellite data

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ABSTRACT - *Regional scale vegetation monitoring and yield forecasting require the estimation of biophysical parameters, such as Leaf Area Index (LAI), biomass and canopy water content (CWC). The CWC is also targeted for fire risk and drought monitoring. This work presents a methodology for jointly retrieval of Canopy Water Content (CWC) and Leaf Area Index (LAI) from coarse resolution satellite data. The method combines the use of databases generated by radiative transfer models (PROSAIL) and powerful nonlinear regression approaches. The advantage of physical models is that they can be coupled each other, thereby providing a physically-based linkage between optical data and biochemical or structural state variables. Suitable parameter combinations of leaf and optical properties were used as inputs into the model to avoid unrealistic simulated spectra.*

## 1 INTRODUCTION

Leaf area index (LAI), defined as the one-side area of leaves per unit of ground area (m2/m2) (Jonckheere et al., 2004) and Canopy Water Content (CWC), defined as the total mass of the liquid water per unit ground area (kg/m2) (Cheng et al., 2008; Trombetti et al., 2008), are a key biophysical variables in agricultural and forestry applications.

Several studies have proved the relationship between canopy reflectance and biophysical parameters (Pasoli et al., 2010; Lázaro-Gredilla et al., 2014) such as LAI and CWC. In particular, the estimation of CWC from optical sensors is related to the water absorption features.

SEVIRI/MSG is a geostationary meteorological satellite system that provides much higher frequency of observation of the land surface than sun-synchronous systems. MSG SEVIRI bands are potentially suited to produce timely information on canopy water status and stress (Fensholt et al., 2010) due the potential of using water absorption band at 1640 nm for the retrieval of CWC.

We propose a retrieval method based on the inversion of a radiative transfer model PROSAIL (Jacquemoud et al., 2009), for the estimation of LAI and CWC maps from SEVIRI/MSG data.

## 2 METHODOLOGY AND DATA

### 2.1 Simulation

For the simulation of the SEVIRI spectra we considered a leaf optical properties model PROSPECT (Jacquemoud and Baret, 1990) coupled with SAIL (Verhoef, 1984), a 1D turbid medium model for the canopy. This coupled modelling scheme called PROSAIL has been used in several remote sensing studies and has already been applied with success in a variety of crops (Duan et al., 2014).

The PROSPECT model simulates the leaf hemispherical transmittance and reflectance as a function of four structural and biochemical leaf parameters: leaf structure parameter N (unitless), equivalent water thickness $C_w$ (g cm$^{-2}$), dry matter content $C_m$ (g cm$^{-2}$) and leaf chlorophyll a + b concentration $C_{ab}$ (μg·cm$^{-2}$). These leaf optical properties simulated by the PROSPECT model are the inputs of the SAIL model. The SAIL model simulates the top-of-the-canopy reflectances as a function of eight input parameters: LAI (m$^2$/m$^2$), average leaf angle ALA (°), fraction of diffuse incoming solar radiation *skyl* (unitless), soil reflectance, hot-spot size parameter *hot* (m·m$^{-1}$), sun zenith angle $t_s$ (°), sensor viewing angle $t_o$ (°), and relative azimuth angle phi (°) between the sensor and sun.

The PROSAIL model was run in forward mode to simulate canopy reflectance on three SEVIRI spectral channels (0.6, 0.8 and 1.6 µm). 1000 parameter combinations were randomly generated with uniform distributions and were used to simulate the spectra. The specific ranges for the variables are shown in Table 1.

Table 1. Ranges of the input variables for the PROSAIL model.

| **Parameter** | **Min** | **Max** |
|---|---|---|
| $C_w$ ($g \cdot cm^{-2}$) | 0 | 0.08 |
| $C_m$ (relative) | 0.05 | 0.50 |
| $C_{ab}$ ($\mu g \cdot cm^{-2}$) | 20 | 30 |
| LAI ($m^2/m^2$), | 0 | 8 |
| *hot* ($m \cdot m^{-1}$) | 0.001 | 1 |
| *Soil* (unitless) | 0.7 | 2.3 |

For leaf structure parameter N and average leaf angle ALA fixed values were chosen according to the values reported in the literature. (N=1.5, ALA=45º)

## 2.2 Inversion

Many methods including neural networks have been used for reflectance model inversion (Baret *et al.*, 2007) and for estimation of CWC (Cernicharo *et al.*, 2013).

Recently a new machine learning approach, based on the Gaussian Process (GP) theory, has been introduced in the literature (Rasmussen and Williams, 2006). According to this approach, the learning of a machine is formulated in terms of a Bayesian estimation problem, assuming that the parameters associated to the machine are a priori jointly drawn from a Gaussian distribution.

The inversion of the PROSAIL model was performed to estimate CWC and LAI. We proposed the use of Gaussian Process Regression (GPR) for canopy parameter retrieval. GPR is a nonparametric method that learns the relationship between the reflectance and canopy parameter by fitting a flexible nonlinear model directly from the data (Verrelst et al., 2012). In general, GPR provides better estimation accuracies than other machine learning algorithms (Lázaro-Gredilla et al., 2012) and may be of particular interest because they do not only provide pixel-wise predictions but also confidence intervals for the prediction.

Figure 1 shows the scatterplot between the simulated data and predictions for the CWC. Model's performance was evaluated with the root-mean-squared error (RMSE), and Pearson's correlation coefficient (R) to account for the goodness-of-fit.

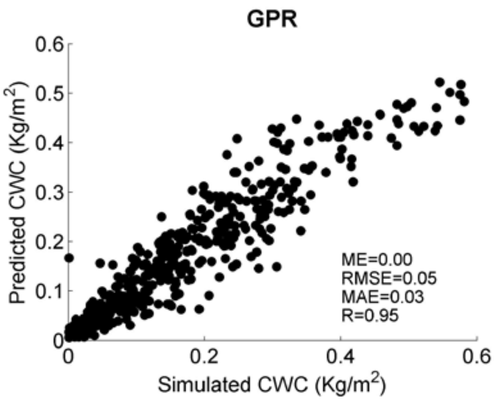


Figure 1. Simulated and predicted CWC

## 3 RESULTS

Extracting the relationship between the reflectance and canopy parameter, Gaussian Process Regression (GPR) provides an estimated map for LAI and CWC. Moreover it provides the variance associated to each pixel that can be interpreted as a confidence of the estimated parameter. Tree bands (0.6, 0.8 and 1.6 µm) of the SEVIRI/MSG reflectance given by the $K_0$ BRDF parameter were used for the GPR.

The retrieved maps for LAI and CWC corresponding to 2013 June the 11$^{th}$, are shown in the following figures.

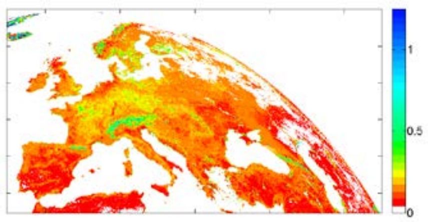


Figure 3. Canopy water content ($Kg^2/m^2$) estimated map retrieved with GPR (2013 June the 11$^{th}$ ).

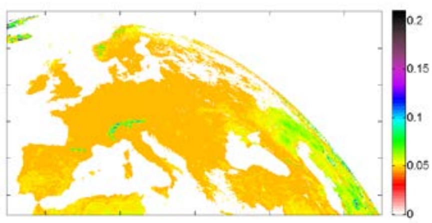


Figure 4. Confidence map (σ) retrieved with GPR for canopy water content ($Kg^2/m^2$) (2013 June the 11$^{th}$ ).

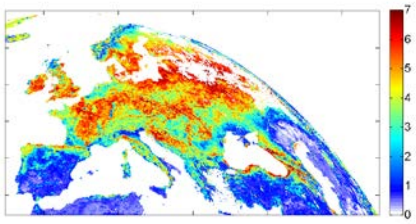


Figure 5. Leaf area index (m $^{2}$/m$^{2}$) estimated map retrieved with GPR (2013 June the 11$^{th}$ ).

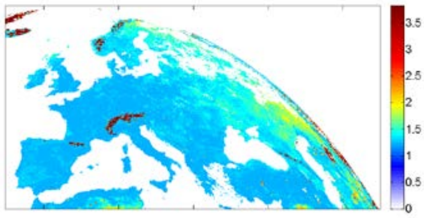


Figure 6. Confidence map (σ) retrieved with GPR for leaf area index (m $^{2}$/m$^{2}$) (2013 June the 11$^{th}$ ).

## 4 QUALITY ASSESMENT

The retrieved LAI and CWC maps have been assessed through the comparison with ground measurements and operational products of biophysical parameters.

The SEN2Exp ground vegetation data set was used in order to perform a direct validation of the results obtained for CWC and LAI through the GPR. Indirect validation was performed comparing the estimations for LAI with Copernicus Global Land LAI GEOV1 product downloaded through the Copernicus Global Land Service. The LAI product is derived at 10-day temporal frequency. More details about the GEOV1 product are available on the following website (http://land.copernicus.eu/global)

### 4.1 Field campaign

As a part of SEN2Exp campaign supported by European Space Agency (ESA) for obtaining data to simulate the instruments on board Sentinel-2 satellite, a field campaign took place over Hart forest (France) between 11-12 of June, and 3-4 of September both conducted in 2013 (Sanchez et al. 2014).

In-situ vegetation characterization includes the sampling of the following variables: Leaf Area Index (LAI), Fraction of Absorbed Photosyntetically Active Radiation (FAPAR), Fraction of green Vegetation Cover (FCOVER), Fresh Weight (FW), Dry Weight (DW) and leaf area (A). LAI, FAPAR and FCOVER parameters have been obtained by using digital hemispheric photography (DHP), taking 12-15 pictures for Elementary sampling unit (ESU).

CWC was derived from the Leaf Area Index and the Leaf Water Content (LWC) as follows:

$$\mathrm{LWC} = \frac{\mathrm{FW} - \mathrm{DW}}{A} \quad [Kg \cdot m^{-2}] \qquad (1)$$

$$\mathrm{CWC} = \mathrm{LAI} \cdot \mathrm{LWC} \quad [Kg \cdot m^{-2}] \qquad (2)$$

Table 2. Comparison of LAI and CWC values with SEN2Exp and Copernicus product over Hart forest.

| HARTH FOREST | | | | | |
|---|---|---|---|---|---|
| DATE | LAI (m$^2$/m$^2$) | | | CWC (kg/m$^2$) | |
| | GPR | GEOV1 | SEN2Exp | GPR | SEN2Exp |
| 06/11/2013 | 5.23 | 4.89 | 4.5 | 0.70 | 0.62 |
| 09/04/2013 | 2.55 | 2.79 | 3.8 | 0.41 | 0.55 |

To validate LAI estimates in a time series, we compared retrieved LAI values with Copernicus Global Land LAI GEOV1 product over 2013 (see Figure 7). Regarding CWC, there is no consistent product available to compare, nevertheless we can compare CWC estimates with ground measurements (see Figure 8). Note that error bars in Figure 7 and Figure 8 refer to RMSE of the Transfer Function used for the up-scaling process based on in situ measurements.

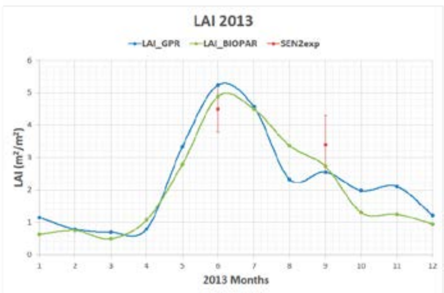


Figure 7. Comparison of the estimated LAI and Copernicus LAI GEOV1 over the 2013. Red points corresponding to ground measurements over Hart forest.

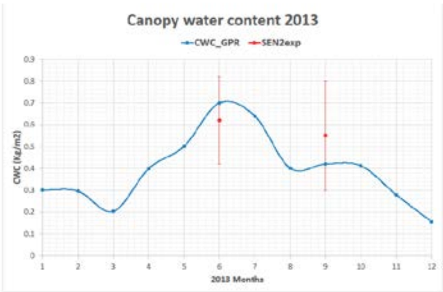


Figure 8. Comparison of the estimated CWC over the 2013 and SEN2Exp campaign. Red points corresponding to ground measurements over Hart forest.

## 3 CONCLUSIONS

This study using MSG/SEVIRI data has explored the possible use of three of its spectral channels (0.6, 0.8 and 1.6 µm) for the estimation of CWC and LAI through the inversion of the PROSAIL radiative transfer model. Time series shows consistency of LAI GPR retrievals with Copernicus GEOV1 LAI product and the very limited ground measurements currently available. Results presented above indicate that the use of the MSG/SEVIRI data can be useful for the CWC and LAI retrieval. Producing CWC and LAI estimated maps using GPR provides also a confidence level for the predictions.

Due to the high dependency of the parameter distribution used as input into PROSAIL, future work includes exploring various parameter distribution on RTM models for improving the database of simulated reflectance. Implementing a regression on multi-output parameter could be evaluated. Consider including other field campaigns will be useful to better validate the estimations.

## 4 ACKNOWLEDGMENTS

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