Inverting a Canopy Reflectance Model Using an Iterative Optimization Technique to Retrieve Canopy Chlorophyll Content

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Abstract

Canopy chlorophyll content provide vital information about exchanging of energy between vegetation and surrounding environment. This study proposed a method to extract canopy chlorophyll content of rice in northern part of Iran form multispectral sensor AVNIR-2 on board ALOS satellite. A field campaign was carried out in June 2010 and several biophysical and biochemical parameters were measured in rice fields. The well-known canopy radiative transfer model PROSAILH was inverted by using iterative method. To assess model inversion performance, RMSE and R2 between independent in situ measurements and estimated canopy chlorophyll content were used. Results demonstrate a proper agreement between estimated and measured canopy chlorophyll content (R2=0/57).

Key words: Remote Sensing, Model Inversion, Chlorophyll, iterative optimization, PROSAILH.

1. Introduction

Remote sensing data in reflective optical domain function as a unique source for providing spatially and temporally information on key biophysical and biochemical parameter of land surface vegetation. Chlorophyll content is strongly related to photosynthetic capacity and productivity (Barry, 2009). The development of precision agriculture has also fueled the need for remote sensing of plant pigments. Since chlorophyll concentration is connected to nitrogen, it has become a key measurement parameter in plant canopies (feret et al, 2008; Gitelson et al, 2002; Ustin et al, 2004).

There are three approaches to estimate Chlorophyll via remote sensing. 1) In the empirical/statistical approach, statistical techniques are used to obtain a correlation between the target variable and its spectral reflectance or some vegetation indices (Darvishzadeh et al, 2008). The derived statistical relationships are recognized as being sensor specific and dependent on site and sampling condition, and are expected to change in space and time (Darvishzadeh et al, 2008; colomb et al, 2002). 2) Visible wavelength is strongly absorbed by foliar pigments. This energy dissipated as heat or reemitted as chlorophyll fluorescence (ChlF). ChlF emission represents only 2-3% of leaf electromagnetic reflectance in the red and NIR spectral regions. Although extracting vegetation solar-induced fluorescence have been tested in laboratory scale, but using such methods for airborne and satellite based sensor is under development and it is not common for practical use in remote sensing community

(Malenovsky et al 2009). 3) Physical models which are based on the inverted use of radiative transfer (RT) models are relevant alternative to statistical and fluorescence approaches. These models describe photon propagation through leaf, canopy, soil and atmosphere based on physical law, thus they can provide explicit connection between at-sensor reflectance and biophysical and biochemical variables. RT models are mathematically invertible if the solution of the inverse problem to be solved, exist, is unique and depends continuously on data (Dorigo et al. 2007). However measurement and model uncertainty are often leading to a large range of possible solutions, which prohibits the inversion to be properly solved and may lead to ill-posed problem (Koetz et al, 2005; Combal et al, 2002; Atzberger 2004). The measurement uncertainties are related to processing of the raw data including radiometric and geometric correction and in situ measurements (Houborg, 2009). Models uncertainty results mainly from the assumption on the canopy structure and optical properties that not fully verified when compared with those of actual canopies (Koetz et al, 2005).

For model application rice was used in this study, as it is of high economic importance in the study area. The goal was to obtain reliable estimate of rice variables (LAI, chlorophyll content). The well-known canopy RT model, PROSAILH, which is the coupled version of leaf model, PROSPECT (Jacquemoud, 1990), and canopy model, SAILH (Verhoef, 1984, 1985; kuusk, 1991), was used to extract these variables from optical sensor AVNIR-2.

2. Data and Material

2.1. Filed experiment

During June 29 – July 14, 2010 an extensive field campaign was conducted in Amol, northern part of Iran. Most of the agricultural activities in this area are characterized by rice crop. Sixty plots of 30m by 30m were chosen by adopting stratified random sampling. In each plot, three to five sub plots of 1m by 1m were randomly selected (depending on the homogeneity of sample plot).

The amount of chlorophyll in each subplot was measured by using a SPAD-502 leaf chlorophyll meter. SPAD values are unit less and have to convert to leaf chlorophyll content (ug cm-2) by means of an empirical calibration function provided by Markwell et al. (1995). Although Markwell function refers to corn leaves, studies have demonstrated that they can be applied to other plant species (Darvishzadeh et al 2008). Leaf area index (LAI) was also measured for each subplot destructively and by using an LI 3000 instrument.

2.2. Preprocessing of image

The ALOS platform was successfully launched by JAXA (Japanizes aerospace exploration agency) on January 26 2004 and contains optical AVNIR-2 sensor, PRISM camera for stereo mapping and PALSAR.

An image of AVNIR-2 (July 7, 2010) was processed since JAXA does not deliver AVNIR-2 images atmospherically corrected; the image was corrected by FLAASH module installed with ENVI 4.7 software. FLAASH incorporate the MODTRAN4 radiation code. The final output of FLAASH is image reflectance. Geometric correction was done with second-degree polynomials, using both the 1:25000 topographic map and handheld GPS-derived control points.

3. Research Methodology

3.1. PROSAILH

The choice of canopy radiative transfer model must satisfy at least two constraints (Atzberger et al, 2003):

- It must allow a fair representation of radiative transfer in the canopy
- It must also be associated with rather limited number of input variables and small computational requirements to facilitate the study.

too many kinds of such a model exist, a good review of these models was presented by (Dorigo eta al, 2008).

3.1.1. Leaf optical model

At leaf level, PROSPECT model (Jacquemoud & Baret, 1990) over 450-2400 nm spectral domain simulates bi-Lambertin reflectance (refl) and transmittance (tran). Input variables include leaf mesophyll structure parameter (N), chlorophyll a and b content (Cab), dry matter (C_{dm}), and water (C_w). The model could then be written as function of its input variables:
[refl,tran]=PROSPECT (N, C_{ab}, C_{dm}, C_w).

3.1.2. Canopy optical model

The SAILH model (Verhoef, 1984, 1985, Kuusk, 1991) is one of the earliest model that simulates top of canopy reflectance given observation geometry, canopy structure, leaf optical properties and soil reflectance (see Jacquemoud et al, 2009. For more detail). Leaf optical properties are simulated by PROSPECT; canopy structure variables are leaf area index (LAI), average leaf angle (ALA) and hot spot size (HOT) which is a function of LAI and fraction of diffuse incoming solar radiation, *skyl*. Therefore SAIL model simply writes:
P^{toc}= SAIL (refl, tran, LAI, ALA, HOT, Rs, θ_s, θ_v, φ)
Where θ_s and θ_v are sun and view zenith angle, φ is azimuth between both directions. Rs is the background reflectance, to account for the change induced by by moisture, observation and illumination geometry and roughness. We used a soil brightness parameters (Darvishzadeh. 2008; Lauvernet et al, 2008 Atzberger. 2003 ;). Thus the Rs is the product of typical soil reflectance (Rs^*) times *Bs* :
$Rs = Bs.Rs^*$
Therefor when two models are coupled, 12 inputs parameter considering the leaf, canopy and soil have to be specified.

3.2. INVERSION

The iterative optimization method is the classical technique to invert physical model. It searches for the best fit between simulated and measured spectra by iteratively running model whit different set of variables. Stopping criteria of iteration is a function known as cost function. There are several cost function used in the literature. A good review of this function can be found in (Liang, 2004). The function that we used is:

$$\mathrm{RMSE_r} = \sqrt{\frac{\sum_{i=1}^{n}(R_{measured} - R_{simulated})^2}{n}}$$

Where $R_{measured}$ is the measured reflectance at wavelength λ and $R_{simulated}$ is simulated reflectance.

4. Results and Analysis

Figure1 illustrates the relation between measured and simulated rice variables using iterative optimization method. The R^2 and RMSE between measured and simulated canopy chlorophyll content shows poor relationships which can be count as the effect of ill- posed problem.

In general, estimating leaf chlorophyll content from physical models was difficult. this confirms other studies (Baret and jacqumoud, 1994; Curran et al. 1992; Darvishzadeh et al. 2008; Weiss et al. 2000a). According to Baret in Liang, 2004, Estimating canopy variables from remote sensing measurements is always an under-determined problem, the number of unknowns is generally larger than the number of independent radiometric information remotely sampled by sensors .

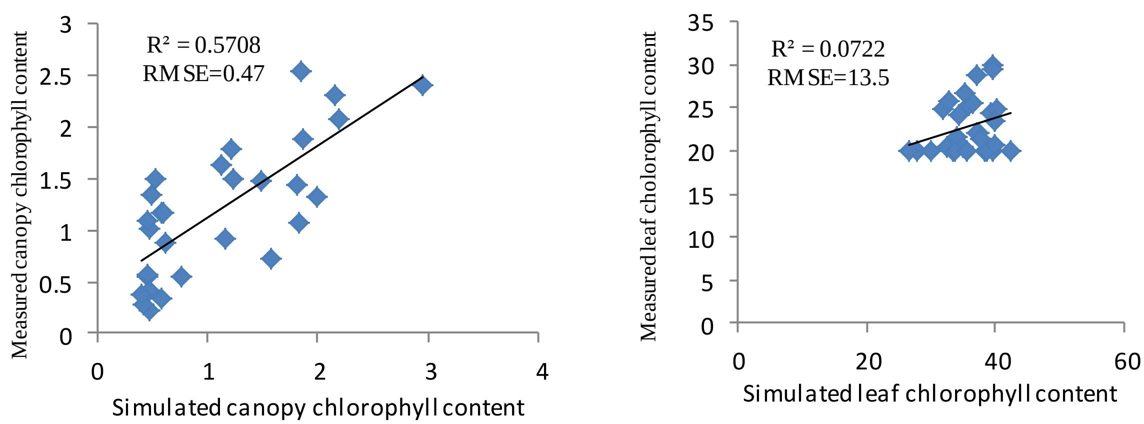

Fig.1 Simulated (estimated) vs measured canopy chlorophyll content (left) and leaf chlorophyll content (right).

For instance in PROSAIL model there is 13 unknown that should be estimated from 4 bands (as a case of ALOS), one direction (nadir) and one snap shot; this is obviously and under-determined problem. In case of the leaf chlorophyll content ill-posed problem cause the estimated value reached their upper or lower boundary (Fig.2).

One way to solve the ill-posed problem is the combination of single variables into synthetic variables such as canopy chlorophyll content which as the product of leaf chlorophyll content and the leaf area index (Dorigo et al. 2007). In our study canopy chlorophyll content estimated with an acceptable accuracy. This is probably due to modulating canopy reflectance by LAI and leaf chlorophyll content (Darvishzadeh et al. 2008).

Since the SAIL model was developed for crops with homogenous canopy cover, the performance of the PROSAIL model is better at time of complete canopy closure than early stage of growth. This is especially important for rice crops, because in early stage the crop lands are inundated and will affect strongly the reflectance of crops in near infrared spectral region. This is confirmed when some points ware recognized as outlier when they were in the early stage of growth.

5. Conclusions

Widely used PROSAILH model was rather successful in this study and by using ALOS multispectral images. Inversion of the model was based on the iterative optimization method. This inversion method is too time consuming. In our case for 44 samples it takes 18 hour to run the program. Thus another inversion method such as look-up table approach and neural network would be a good alternative of iterative optimization method.

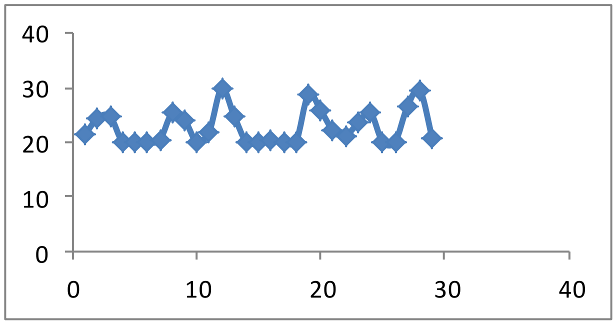

Fig.2. Scatter plot of simulated leaf chlorophyll content

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