SEASONAL LAI ESTIMATION OF IRRIGATED RICE USING SOIL-LEAF-CANOPY (SLC) RADIATIVE TRANSFER MODEL

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ABSTRACT This study compared the use of both the MODIS LAI (MOD15A2) product, which provides directly the 8-day LAI at 1km spatial resolution, and the MODIS 8-day surface reflectance product (MOD09A1) in retrieving and estimating the seasonal variation of LAI for irrigated rice in the Mekong delta, Vietnam. The Soil-Leaf-Canopy (SLC) radiative transfer model was employed to invert MOD09A1 reflectance spectra to get LAI estimates through the look-up table (LUT) approach. The result showed that the dynamic evolution of LAI of irrigated rice during one cropping season could be estimated fairly well by the SLC model (R^2 = 0.69, RMSE= 0.9). This result is a great improvement compared to the retrieved LAI from MOD15A2 (R^2 = 0.07, RMSE = 2.1).

INTRODUCTION

Remote sensing data can be exploited for the retrieval of land surface variables, such as leaf area index (LAI) and the fraction of absorbed photosynthetically radiation (fAPAR). These are key biophysical parameters in most ecosystem productivity models and in global models of ecology and climate (Myneni et al., 1997). LAI can be retrieved from remotely sensed data through the use of (i) statistical approach based on empirical relationships between *in situ* LAI and Vegetation Indices (VI) (Gupta et al., 2000; Myneni et al., 1997; Turner et al., 1999), and (ii) physical approaches based on the inversion of a canopy radiative transfer model (Combal et al., 2003; Kimes et al., 2000). However, as LAI estimation based on the statistical often suffers from saturation and a low sensitivity of the VI at high values of LAI (Baret & Guyot, 1991), and the relationship very much depends on time, location and vegetation type (Baret & Guyot, 1991; Colombo et al., 2003), it lacks generality and consequently is hardly applicable to large-scale operation. Canopy radiative transfer models (RTMs), on the other hand, describe the interaction between solar radiation and vegetation elements inside the canopy and the background surface. The models calculate the Top-Of-Canopy (TOC) reflectance as a function of vegetation characteristics, by physical laws (Meroni et al., 2004), and hence they are able to provide explicit relationships amongst TOC reflectance and the vegetation's physical and biochemical properties (Houborg et al., 2007). LAI estimation by inverting RTMs is a very promising approach. Inversion of canopy RTMs can be done through the Look-Up Table (LUT) approach (Combal et al., 2003; Darvishzadeh et al., 2008). A LUT-based method is very simple and easy to implement. It also can overcome the huge demand of computation time required by RTM inversion (Liang, 2004).

For decades, the use of RTMs to retrieve rice LAI is rarely seen. To improve this gap in knowledge, our research tried to investigate the inversion of a coupled soil BRDF - canopy radiative transfer model to simulate seasonal LAI for irrigated rice. We also tested if the MODIS LAI product (MOD15A2) provided directly by NASA at could be successfully used for rice monitoring.

MATERIALS

Study area

The study area was located in the largest rice producing area of the Mekong Basin, the Mekong Delta in Vietnam. Rice is often cultivated in a double or a triple cropping system. Figure 1 shows the geographical location of the Mekong delta, and its rice cropping patterns throughout a year. The rectangular box presents the studied site. The map was derived from SPOT-NDVI 1km resolution data.

To obtain *in situ* LAI, 60 rice paddies were selected based on a random stratified sampling scheme. Two important criteria of the sampling are (i) type of rice cropping system, and (ii) type of cultivated rice varieties. The 60 selected fields were all located in areas where either a double or a triple rice cropping system was practiced.

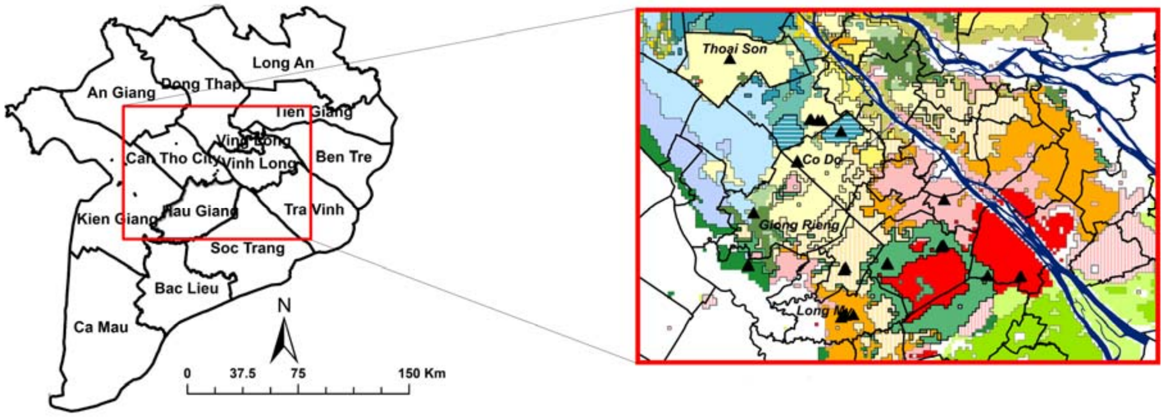

Figure 1. Administrative map of Mekong delta, Vietnam with the location of the studied sites and their rice cropping patterns.

MODIS data

MOD15A2 is the 8-day LAI/FPAR product at 1km resolution he MOD15A2 LAI The latest version 5 MOD15A .V005 data were downloaded for the period Nov 2008 – May 2009. The data covers a complete rice growing season in all observed paddy fields.

MOD09A1 is the 8-day surface reflectance product derived from MODIS Terra daily observations. MOD09A1 is atmospherically corrected, and contains the best possible pixel-values of daily observation (L2G) during an 8-day period as selected on the basis of high observation coverage, low view zenith angle, the absence of clouds or cloud shadow, and aerosol loading. These are 500m resolution data with 7 bands covering the spectral range 459 – 2155 nm. All seven bands of MOD09A1 were used as inputs for inversion of a RTM. Only MOD09A1 pixels with good quality and without cloud effects were considered for analysis. Bad and fill-value pixels were assigned a value of 0.

***In situ* measurements**

In situ LAI measurements were conducted in 60 different rice paddies during the winter-spring cropping season (November – May). These measurements were taken from December 2008 to May 2009. LAI was measured using the LI-COR LAI 2000 Plant Canopy Analyzer. Selected rice paddies were located in the centre of relatively homogenous rice cropping pattern areas as mapped in Figure 1. Every 7 – 10 days, each paddy field was revisited for the LAI measurement. At each visit, LAI measurements were taken at 1m by 1m plots along a diagonal transect of each field, and were later averaged to get a field-representative LAI value.

Leaf chlorophyll content of rice was measured at the same time as LAI measurement using the Minolta SPAD 502 Meter. Thirty SPAD readings were made at each 1m by 1m subplot and then averaged into one value corresponding to each LAI measurement. These average SPAD readings were converted into leaf chlorophyll content (C_{ab}) by means of an empirical calibration equation suggested by Markwell *et al.* (1995).

Table 1. Summary statistics of measured biophysical and biochemical variables for rice

Variable	Min	Max	Std.
LAI ($m^2. m^{-2}$)	0.9	7	1.3
SPAD (*unitles*)	16.6	53.7	4.7
Leaf chlorophyll content ($\mu g.cm^{-2}$)	11.5	67.2	6.7

METHOD

Comparison of in situ LAI and MOD15A2

As the *in situ* LAI measurements had a time resolution of around 10 days, in order to be compared to MOD15A2 8-day LAI, *in situ* LAI must be interpolated. The interpolation was done using a LAI dynamics model, which is a function of daily mean accumulated temperature, as quoted by Koetz et al. (2005).

$$LAI = LAI_{amp}\left\{\frac{1}{1+\exp[-b(T-T_i)]} - \exp[-a(T-T_s)]\right\} \quad \textbf{Equation 1}$$

where T is accumulated daily mean air temperature (above a base temperature of 8^0C for rice) starting from sowing date; b is relative growth rate at accumulated temperature T_i (the first inflexion point); a is relative senescence rate at accumulated temperature T_s (at the time of green leaves disappearance).

MOD15A2 has a spatial sampling of 1km x 1km and since a rice paddy could lay on two different MOD15A2 pixels, a weighted sum based on the percentage of field area proportion was applied to obtain one single representative LAI value for that field.

The SLC model

The SLC model (Verhoef & Bach, 2007) is a coupled soil-leaf-canopy radiative transfer model. The model consists of three sub-models, which are (i) a modified Hapke soil BRDF model, (ii) the PROSPECT leaf model, and (iii) the 4SAIL2 canopy RTM including two layers and crown clumping.

The modified Hapke bi-directional reflectance (BRDF) model in SLC describes the soil's interaction with the canopy by means of two four-stream radiative transfer equations, using all combinations of hemispherical and directional radiation. For irrigated rice, since the paddies are flooded during most of rice growing season, additional spectral reflectance information of turbid water on the field is required.

The input parameters of PROSPECT and 4SAIL2 are shown in Table 2.

Table 2. Set of input parameters for SLC model used to estimate rice LAI

Parameter	Unit	Value	Parameterization
Green leaf mesophyll parameter	-	1.5 – 1.8	Step of 0.1
Green leaf chlorophyll concentration	$\mu g.cm^{-2}$	16.6 – 53.7	Step of 5.5
Green leaf water content	cm	0.01 – 0.02	Step of 0.005
Green leaf dry matter content	$g.cm^{-2}$	0.005 – 0.01	Step of 0.0025
Green leaf brown pigment	-	0.15	Fixed
Brown leaf mesophyll parameter	-	2	fixed
Brown leaf chlorophyll concentration	$\mu g.cm^{-2}$	0	fixed
Brown leaf water content	cm	0	fixed
Brown leaf dry matter content	$g.cm^{-2}$	0.01	fixed
Brown leaf brown pigment	-	2	fixed
Leaf area index	$m^2.m^{-2}$	0 – 7	Step of 0.1 for LAI ≤ 4; 0.2 for 4 ≤LAI ≤5; and 0.5 for 5 ≤ LAI ≤ 7
Leaf inclination distribution function parameter *a*	-	-0.65; -0.5; -0.35	
Leaf inclination distribution function parameter *b*	-	-0.15; 0; 0.15	
Hotspot size	$m.m^{-1}$	0.1/*LAI*	
Fraction brown leaf area(*)	-	0.01 – 0.1	1 random value for each LUT run

Dissociation factor[(*)]	-	0.4 – 1	1 random value for each LUT run
Vertical crown cover fraction	-	1	
Tree shape factor	-	0	
Solar zenith angle	deg	0 - 90	MOD09A1 data set
Viewing zenith angle	deg	0 – 90	MOD09A1 data set
Relative azimuth angle	deg	0 - 180	MOD09A1data set

[(*)] *Parameters estimated based on field observations and photos taken in the field.*

LAI estimation based on the look-up table inversion

The LUT approach consists of two major steps: (i) the generation of the LUT itself, based on regular intervals or random selection from a uniform distribution of specific ranges of the respective model parameters; and (ii) applying the LUT by selection of the optimum solutions for given referenced data (MOD9A1). For every 8-day composite set of MOD09A1 imagery, a LUT consisting of approximately 110,000 SLC-parameter combinations was generated.

Selection of the optimal LUT inversion solutions were made through the evaluation of the root mean square error (*RMSE*) that measures the difference between the model estimation and referenced data. *RMSE* is calculated by Eq. (2).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n_b} \left(R_{i,ref} - R_{i,j}\right)^2}{n_b}} \qquad \textbf{Equation 2}$$

where $R_{i,ref}$ is the MOD09A1 reflectance at wavelength i and $R_{i,j}$ is the SLC estimation at simulation j at wavelength i in the LUT; n_b is the number of wavelength bands. The best solution was considered having the smallest RMSE value.

RESULTS AND DISCUSSION

Comparison of *in situ* LAI and MOD15A2 LAI

Figure 2 shows the daily interpolation of *in situ* LAI for the period from November 1, 2008 to April 30, 2009. Since the daily temperature never got below the base temperate of 8^0C, the evolution of rice LAI during the growing season was presumably normal, following the dynamics provided in Equation 1. The interpolated LAI for rice based on *in situ* measurements rarely exceeds the value of 6. Maximum LAI values often reached 40 - 50 days before harvest.

For the whole growing season, the relationship between MOD15A2 LAI and *in situ* LAI was found very poor (R^2 = 0.07, RMSE = 2.1). MOD15A2 LAI mostly underestimated rice LAI (Figure 3). This is likely caused by inaccurate input information of the background reflectance in the MOD15A2 RTM, where soil reflection is assumed to have intermediate brightness. It is certainly not true for irrigated rice, of which fields are flooded during most of the growing season. A poor inversion of the MOD15A2 RTM could be one reason that shows the poor relation between MOD15A2 LAI and *in situ* LAI (Huifang et al., 2009).Other reasons might be either due to the use of incorrect land cover information as one of the input of MODIS RTM or the use of back-up algorithm when MODIS RTM failed to produce LAI.

LAI estimation from LUT inversion

The SLC simulated MODIS reflectance spectra on a pixel-by-pixel basis for the 60 rice locations have an RMSE range of 0.021 ± 0.02. Relatively high RMSE values were observed in areas where the crop was either at its very early phenological stage (around 0-10 days after sowing) or at its late reproductive stage (10-15 days before harvest). Non-rice areas, e.g. residential and fallow areas, were found having high RMSE too. This is because in the SLC simulation a water background reflectance was always considered.

The correlation between the SLC inversion simulated LAI and the *in situ* LAI (Figure 5) is much better (R^2 = 0.69, RMSE = 0.9) than that between MOD15A2 LAI and *in situ* LAI (Figure 3). The errors between estimated LAI and measured LAI are evenly distributed on both sides of the 1:1 line. For estimated LAI≥ 6, the agreement between measured and SLC estimated LAI values started to differ systematically, with higher values achieved through SLC. The reason could be, as found by He et al. (2007), the underestimation of true LAI by LAI-2000 due to saturation at high LAI. The mean difference between estimated LAI and MOD15A2 LAI for the whole growing season in this study is 1.4, which is less than what was reported by Cheng (2008) when comparing MOD15A2 LAI and *in situ* LAI at different phenological stages for hybrid rice.

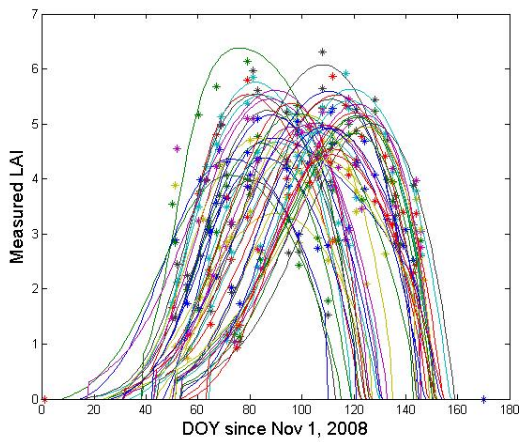

Figure 2. Daily interpolation of *in situ* LAI

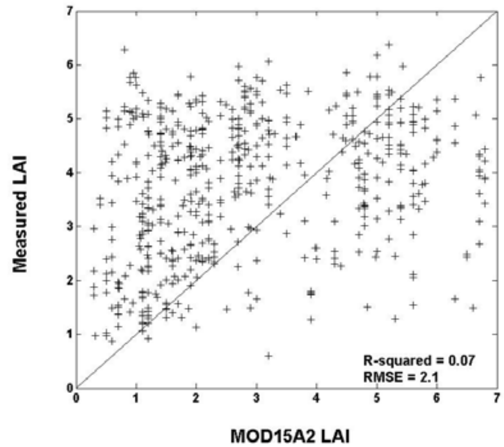

Figure 3. Comparison between retrieved MOD15A2 LAI and *in-situ* LAI.

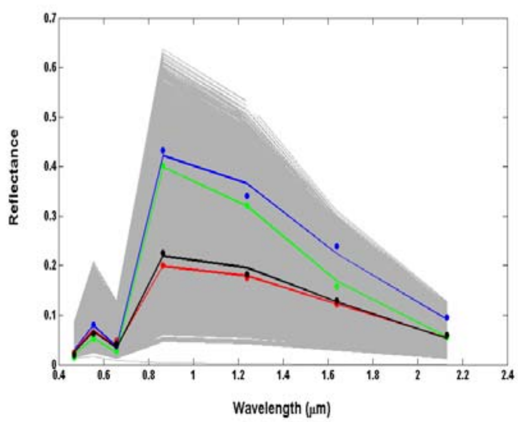

Figure 4. Set of 110,000 random MODIS equivalent synthesis spectra from a single-date LUT generated by SLC

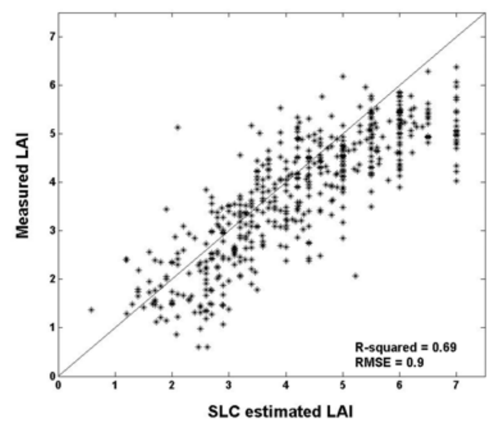

Figure 5. Comparison between SLC stimated LAI by LUT approach and measured LAI.

CONCLUSION

The study has demonstrated the benefit of using the SLC model for dynamic LAI estimation for irrigated rice in the Mekong delta, Vietnam. In extensively rice cultivated areas, the available MODIS LAI product MOD15A2 failed to detect rice LAI evolution with time ($R^2 = 0.07$, RMSE = 2.1), while the use of SLC model for dynamic LAI estimation proves promising to overcome this problem..

LAI estimated by inverting the SLC model was much more accurate than LAI provided by the MOD15A2. Look-up table inversion of the SLC model explained 69% of the variance of *in situ* LAI during the whole cropping season, with a RMSE of 0.9

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