COMBINATION OF CROP GROWTH MODEL AND RADIATION TRANSFER MODEL WITH REMOTE SENSING DATA ASSIMILATION FOR FAPAR ESTIMATION

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ABSTRACT

Accurate assessment of Fraction of Absorbed Photosynthetically Active Radiation (FAPAR) in large scale is significant for crop productivity estimation and climate change analysis. The object of study is to simulate FAPAR in the rice growth period for exploring photosynthetic capacity of rice in large-scale. The daily FAPAR is calculated based on a coupled model consisting of the leaf-canopy radiative transfer model (PROSAIL) and the World Food Study Model (WOFOST). Due to the limitation of the PROSAIL and WOFOST model, we introduced the remote sensing data assimilation method, which assimilated the Normalized Difference Vegetation Index (NDVI) into the coupled model, to improve the prediction accuracy and carry out the large-scale application. The results show high correlation between the simulated FAPAR and the measured data, with the determinate coefficient (R^2) of 0.75 in the study area. The spatial distribution of FAPAR is uniform in flat area, which indicates that the rice in the whole study area has well growth condition and photosynthetic capacity. This study suggest that the coupled model (PROSAIL + WOFOST) assimilated with remote sensing data could accurately simulate daily FAPAR during the crop growth period.

Index Terms— FAPAR, crop model, PROSAIL, coupled model, assimilation

1. INTRODUCTION

The crop productivity is largely determined by the amount of intercepted solar radiation and the efficiency of photosynthesis process (which means the conversion efficiency of intercepted energy to carbohydrates)[1]. The Fraction of Absorbed Photosynthetically Active Radiation (FAPAR), defined as the fraction of Photosynthetically Active Radiation (PAR) absorbed by a green canopy in the 0.4–0.7 μm spectral range, provides the key information for quantitative estimation of canopy photosynthetic capacity as it constrains the photosynthesis rate through the energy absorbed by the vegetation[2]. In addition, FAPAR has been proven to be a crucial biophysical variable in characterizing energy conversion of crop physiological process and an important indicator for monitoring the health status of crop growth[3]. However, crop growth is a dynamic process and the instantaneous FAPAR could not reflect the crop growth condition during the whole growth period. Therefore, it is necessary to simulate FAPAR seasonally by the agricultural sector to properly assess the health status and productivity.

Studies indicate that the estimation of FAPAR from optical remote sensing data can be divided into empirical and physical methods [4-6]. The empirical methods are widely used , which mainly focus on empirical relationship between field-measured FAPAR and satellite-derived vegetation indices by regression analysis[7]. This method needs no knowledge of physical mechanism in the radiative transfer process, which makes it easy to apply in large areas.[8]. However, the empirical model are limited by conditions because the canopy reflectance changes with observation and spatial resolution[8]. Some studies demonstrate that the relationship between FAPAR and vegetation indices, such as NDVI, is seriously affected by vegetation growth period and the reflectance of background[9]. In contrast, the physical model which consider the interaction between solar radiation and vegetation canopies can be applied under most conditions, including different land covers and growth periods[6]. However, the physical models require many input parameters for initialization. Some studies conducted sensitivity analysis in the physical model to assess the contribution of the input parameters in FAPAR retrieval[10]. The results show leaf area index (LAI) play a greater role than other vegetation biochemical variables in FAPAR estimation. This study also reveals that the accuracy of LAI estimation directly influences the retrieval performance of physical model. Therefore, LAI could be the significant connection between physical and other models. In addition, both empirical and physical models are discontinuous in temporal scale because of the visit circle of remote sensing data[6]. This limitation result in the missing of time-series of FAPAR. Previous studies found that assimilating LAI into the WOFOST model can simulate seasonal LAI accurately during rice growth period[11]. The variation of rice biochemical parameters have been considered in this method. Hence, the combination of the physical and

WOFOST models with data assimilation is considered as the effective approach to simulate seasonal and large-scale FAPAR for rice photosynthesis assessment.

In this study, the coupled model, consisting of PROSAIL and WOFOST model, is employed to simulate daily FAPAR during rice growth period. Then, NDVI derived from remote sensing data are assimilated into this coupled model to improve the accuracy of FAPAR simulation and obtain FAPAR in large scale. This study aims to simulate FAPAR during the rice growth period to explore photosynthetic capacity in large-scale.

2. STUDY AREA AND DATA

The study area is located in Zhuzhou (112^{0}17'-114^{0}07' E, 26^{0}03'-28^{0}01' N), a city in Hunan Province of China, which is an old industrial base and important grain production region. The climate here is mostly humid, and there is sufficient sunshine for growing paddy rice from May to September. Rice is the major crops in this area. Six sampling point are selected in this study area to obtain measured data for validation.

The experimental datasets include remote-sensing, meteorological and field-measured data. Four 16m multispectral GaoFen-1 images (The first series of Chinese High Resolution Earth Observation System, GaoFen-1) are selected to calculate NDVI for assimilation in the rice growth period. The rice area is extracted by supervised classification. In order to obtain validation data, three fieldworks were carried out to obtain FAPAR of rice in 2015 during the entire rice growing season. In the fieldworks, the FAPAR are calculated from PAR above and below the canopies. The SPAD-502 portable chlorophyll meter (Minolta Corporation, Ramsey, NJ, USA) are employed for PAR measurements. The meteorological data, including daily maximum temperature, minimum temperature, early morning vapor pressure, mean daily wind speed at 10 m and hours of sunshine, are obtained from the China Meteorological Data Sharing Service System to drive the crop model.

3. METHOD

In this study, the PROSAIL and WOFOST model are combined through the crucial variable LAI to obtain FAPAR during the rice growth period. Then we assimilated remote sensing images into this coupled model to simulate FAPAR in large scale.

3.1 Improved PROSAIL Model for FAPAR calculation

We improve the PROSAIL model by the law of conservation of energy for calculating FAPAR. Based on the Four-Stream Radiative Transfer theory developed by Verhoef and Bach, the direct and diffuse directional transmittance and reflectance calculated by PROSAIL are considered in order to assess the absorption efficiency of light by the canopy[12]. Meanwhile, multiple scattering effects caused by the interaction between the canopy and background soil need to be considered in the calculation. The equations for calculating the FAPAR is as follows [12]:

$$\alpha_s^* = \alpha_s + \frac{\tau_{ss}\gamma_{sd}+\tau_{sd}\gamma_{dd}}{1-\gamma_{dd}\rho_{dd}^b}\alpha_d \tag{1}$$

$$\alpha_d^* = \alpha_d + \frac{\tau_{dd}\gamma_{dd}}{1-\gamma_{dd}\rho_{dd}^b}\alpha_d \tag{2}$$

$$\alpha_s = 1-\rho_{sd}-\tau_{sd}-\tau_{ss} \tag{3}$$

$$\alpha_d = 1-\rho_{dd}-\tau_{dd} \tag{4}$$

$$\mathrm{FAPAR} = \frac{\sum_{\lambda=400}^{\lambda=700}(\alpha_s^* E_{dir}^t+\alpha_d^* E_{dif}^t)}{\sum_{\lambda=400}^{\lambda=700}(E_{dir}^t+E_{dif}^t)} \tag{5}$$

where α_s^* and α_d^* are canopy absorptance for direct solar incident flux (E_{dir}^t) and hemispherical diffuse incident flux(E_{dif}^t), respectively; α_s and α_d represent absorbance of the isolated canopy layer for solar and hemispherical diffuse incident flux, respectively; γ_{dd} and γ_{sd} are bi-hemispherical factor and directional–hemispherical factor over the surroundings, respectively; τ_{ss} and τ_{sd} are direct transmittance and directional-hemispherical transmittance for solar flux, respectively; ρ_{dd} and ρ_{sd} represent bi-hemispherical reflectance at top-of-canopy and directional–hemispherical reflectance for solar flux, respectively; ρ_{dd}^b is the bi-hemispherical reflectance at the bottom of canopy. This improvement makes the PROSAIL simulate the reflectance and FAPAR of canopy simultaneously.

3.2 Coupled WOFOST and PROSAIL model with remote data assimilation for large-scale FAPAR simulation

The WOFOST model is a mechanistic model that simulates the annual growth of crop at a daily time-step under specific soil and climate conditions. LAI, as the input parameter of WOFOST and the output parameter of PROSAIL, is the essential variable for crop growth simulation. In this study, we employ LAI as the connection between the PROSAIL and WOFOST model for FAPAR simulation during the rice growth period. However, the WOFOST and PROSAIL model are point-model which only simulates parameters in small scale. And those two models are not well performed in realistic environment because the crop is effect by many factors in the growth period. In which, the transplant date(TD) is the important factor for the accuracy of LAI simulation in the WOFOST model. Therefore, the remote sensing date assimilation is employed for optimizing the coupled model (WOFOST+PROSAIL) in order to obtain FAPAR in large scale. The assimilation process adjusts the TD using particle swarm optimization algorithm (PSO), which calculate the cost function between retrieved NDVI from remote sending data and simulated NDVI from coupled model. The process can be simply divided into four

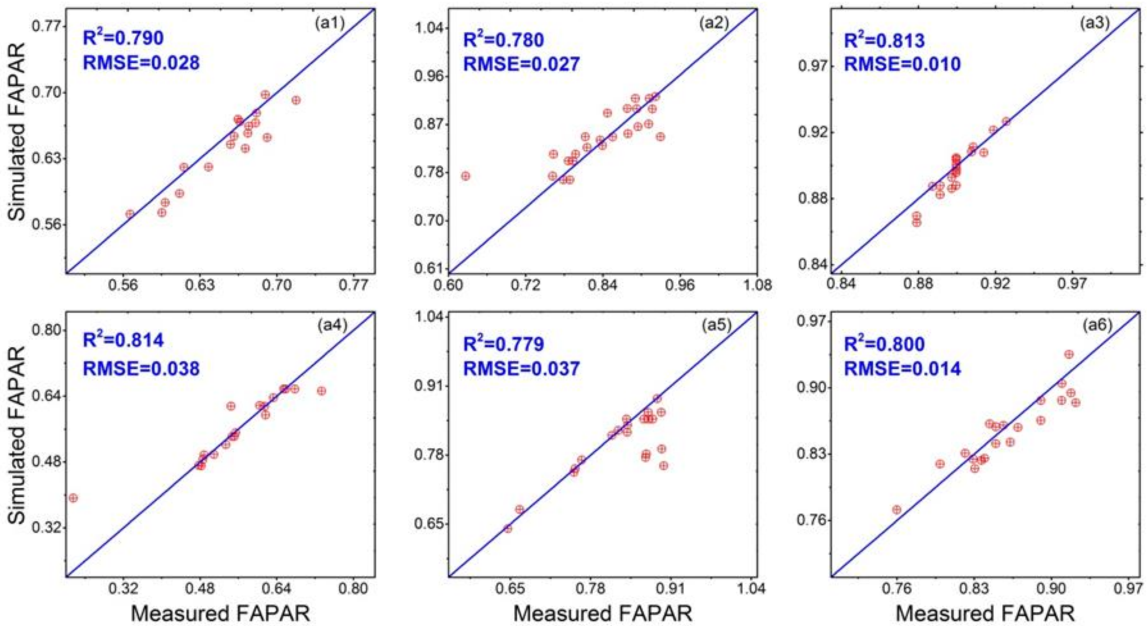

Figure 1 Validation of simulated FAPAR against measured FAPAR at six sampling point

Table 1 Comparison of determinate coefficient (R^2) at six sampling point

Sampling point	a1	a2	a3	a4	a5	a6
R^2 with assimilation	0.790	0.780	0.813	0.814	0.779	0.800
R^2 without assimilation	0.650	0.689	0.700	0.712	0.667	0.702

steps. Firstly, NDVI are retrieved from GaoFen-1 images corresponding to different rice growth period. Secondly, the coupled model is initialized to simulate the NDVI in the whole growth season. Then, the cost function is calculated based on retrieved and simulated NDVI values at the corresponding time. Finally, if the cost function does not meet the condition, the initial TD is continually adjusted until the difference between simulated and retrieved NDVI vale was minimal. The detail of PSO and cost function is described in our previous studies.

4. RESULT

In six sampling points, we obtain the measured FAPAR to verify the accuracy of coupled model. Based on the position of sampling points, the simulated values are selected to compare with the corresponding measured values. Then, the correlations between simulated and measured values are analyzed. In study area, the determinate coefficient (R^2) at six sampling points were 0.790, 0.780, 0.813, 0.814, 0.779 and 0.800 (Figure **1**), respectively. All root mean square error (RMSE) values are less 0.04. Then we simulated FAPAR without assimilation to assess the performance of assimilation in FAPAR simulation. The correlation between measured and simulated FAPAR without assimilation are calculated and compared with that between measured and simulated FAPAR with assimilation process. The result shows that remote sensing data assimilation significantly improves the accuracy of the coupled model (Table **1**). These results suggest that this coupled model combined PROSAIL and WOFOST is an effective tool for FAPAR estimation. And data assimilation can effectively improve the accuracy of coupled model. Based on the validation procedure, the coupled model optimized by remote sensing data assimilation can be used to simulate the FAPAR in large area. It could address the spatial discontinuity caused by the coupled model and temporal discontinuity caused by remote sensing data. FAPAR retrieved from remote sensing data are influenced by meteorological condition in the rice crucial period. But the coupled model and data assimilation could

fix the problem and simulate FAPAR in the whole growing period. The spatial distribution of FAPAR in the heading stage, which is the most vigorous stage of rice growth, is shown in Figure 2. In general, the spatial distribution of FAPAR is stable in Zhuzhou city. In the southern part, mixing pixels are occurred as a result of the complexity of terrain. As a result, FAPAR are higher than those in other areas. In order to eliminate the effect of mixing pixel, it is necessary to employ an accurate classification method for farmland extraction. Besides, we assumed that the input parameter of the crop model and radiative transfer model are invariable, however, these parameters could change and lead to some errors in reality. Therefore, more fieldworks are needed to normalize the parameters to improve the accuracy of coupled model in the future.

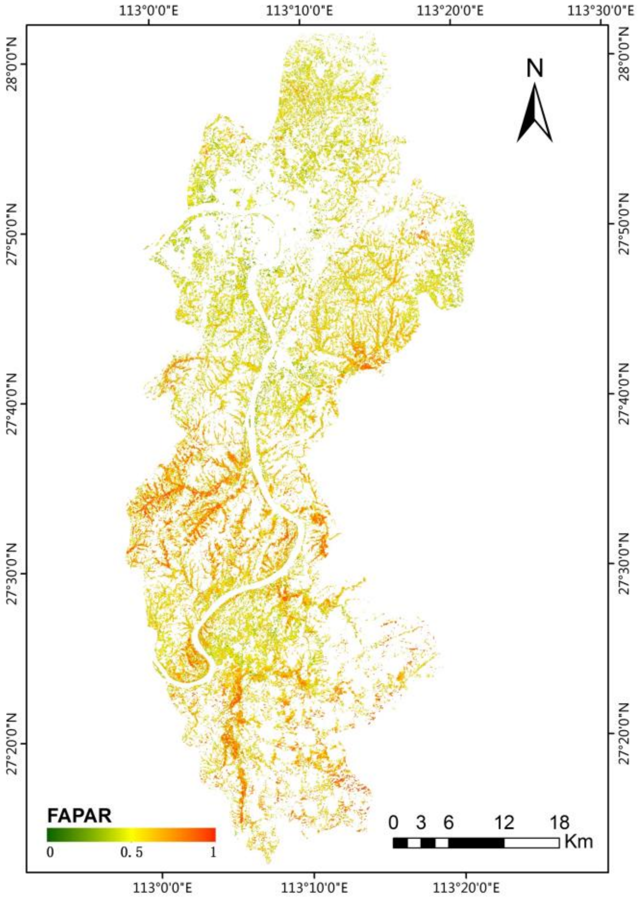

Figure 2 The spatial distribution of FAPAR of rice in heading period

5. CONCLUSION

In this study, the WOFOST and PROSAIL model are coupled for FAPAR simulation during the rice growth period. Then the coupled model is optimized by remote sensing data assimilation which also introduces the coupled model to larger scale. The simulation accuracy of coupled model is assessed by calculating the determinate coefficient (R^2) between simulated values and validation data. The high correlation between simulated and measured FAPAR indicate that the coupled model with data assimilation has high stability and availability. The spatial distribution of FAPAR is uniform in most flat area. But in the mountain area, FAPAR are abnormal higher because of the mixing pixels. Consequently, this coupled model (the PROSAIL and WOFOST model) could be an effective approach to simulate FAPAR accurately in large scale.

6. REFERENCES

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