Assimilation technique of remote sensing information and rice growth model based on particle swarm optimization

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Abstract: The choice of optimization method is very important in the assimilation process of crop growth model and remote sensing data, and it concerns the running efficiency and result accuracy of assimilation. In this study, a new optimization--Particle Swarm Optimization (PSO) technique is used for assimilating remote sensing data and RiceGrow model in minimizing difference between inverted and simulated values by remote sensing and RiceGrow model. We compare PSO with another optimization--Simulated Annealing (SA) and explored the assimilation result when LAI and LNA are used as external assimilation parameters respectively. The results show that PSO performed better than SA in both running efficiency and assimilation result, which indicates that PSO is a reliable optimization method for assimilating remote sensing information and model. LAI and LNA each have advantage as external assimilation parameters, sowing date and seeding rate can be well inverted when LAI is selected as external assimilation parameter, while nitrogen rate is better predicted using LNA. However, the inverted result is better when LAI is employed as external assimilation parameter. Experiment data is used to test the assimilation technique and result shows that the relative errors for initial parameters of growth model and yield are less than 2.5% and 5%, respectively. RMSE values are between 0.7 and 2.2, which indicates that the assimilation technique based on PSO is reliable and applicable and that this new assimilation technique can lay the foundation for crop model application from spot to region scale.

Key words: particle swarm optimization, RiceGrow model, assimilation technique, parameter initialization

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1 INTRODUCTION

Crop growth model based on ecosystem and principle of energy conversion could quantitatively describe crop physiological and ecological processes and their relationship with external environment by means of mathematics and physics methods. It is a kind of mechanism and dynamic simulation model (Yu, 1994). It can predict leaf area index, biomass and yield well at single point (Ye *et al*., 2007, 2008). Crop growth model needs some initial input parameters, including meteorological data, soil data, crop varieties and management technical measures (such as sowing date, density, fertilizing amount). When the multi-point or regional-scale application of crop growth models (such as large area yield estimation) was needed, these initial parameters may be different in each space point, resulting in difficult acquisition for initial parameters on multi-point or regional-scale, which limits the model effective application on large scale. Therefore, the combination of remote sensing technology and crop models is used as key technology for regional application of crop model. Remote sensing can provide timely crop model environmental parameters, so that the simulation is closer to reality, and through production difference analysis, to provide policy recommendations and guidance for higher yield (Wang *et al*., 2005). Furthermore, remote sensing can also provide accurate, real-time information for large area crop growth parameters(Deng, 2002; Wang *et al*., 2002). Therefore, crop growth model (continuous time process) and remote sensing (spatial scale continuous), the two space-time complementary combination are expected to solve the problem that it is hard to acquire initial input parameters used in growth model on regional scale application (Wit *et al*., 2007; Martin *et al*., 2008).

There are a lot of research about the combination of crop growth model and remote sensing technology both at home and abroad, including the drive method which uses remote sensing as model input variables for driving the model and the assimilation method which uses state variables retrieved from remote sensing to calibrate crop model process or re-initialize the crop model for optimization. The research about assimilation method

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based on the combination of crop model and remote sensing information mainly includes optimization algorithms, the choice of parameters to be optimized and the regionalization methods of crop growth model (Ma *et al*., 2005b; Marie *et al*., 2005). Many studies show that the selection of optimization algorithm used in assimilation of crop growth model and remote sensing data is crucial (Yan, 2006). The choice of optimization algorithm could determine the assimilation efficiency and retrieval result accuracy. Zhao *et al*. (2005) used SCE_UA and SA in remote sensing-cotton growth model assimilation to forecast cotton yield, the error of simula- tion being about 5 %. Yan (2006) in the assimilation of remote sensing and CERES_Wheat model used SCE_UA algorithm and achieved good results. Guerif & Duke (1998) used FSEOPT program to get some important parameters (such as sowing, leaf area, *et al*.) needed in SUCROS model in assimilation process to predict the yield of beet. However, the principle of those methods mentioned above is complicated resulting in the difficulty to change algorithm with self-prog- ramming for local application, which, to some extent, limits their application.

Therefore, this article aims to introduce an optimization algorithm with simple principle and could be integrated easily—Particle Swarm Optimization (PSO) (Kennedy *et al*., 1995). Rooted on rice growth model-RiceGrow, we assimilate growth information from remote sensing data to establish a technique for initializing parameters needed by RiceGrow. This technique can extend application of rice growth model from single point to multi-point or region.

2 DATA SOURCES

2.1 Experiment design and data acquisition

2.1.1 Experiment design

Data used in this study come from two rice field experiments, involving different years, different cultivars, different N levels and different density, and the specific experimental designs are as follows.

Experiment 1 was carried out in 2008 on Jiangpu Farm of Nanjing Agricultural University. The experiment was a randomized complete block design with four nitrogen rates and two density rates, using the variety Yanjing9. Four nitrogen rates were established as 150(N1), 240(N2), 330(N3), 420(N4) kg·hm^{-2}. Two density rates were established as D1(planting spacing 20 cm×25 cm) and D2(planting spacing 30 cm×25 cm). Sowing data was May 15th, transplanting data was June 15th and dressing ratios was 5:5. The fertilization of P and K, and other field managements followed the local rice production standard. The experiment plots were arranged in two replications with the plot size of 45 m×90 m area.

Experiment 2 was carried out in 2007 at the experiment station of Nanjing Agricultural Bureau. The experiment was a randomized complete block design with three nitrogen rates, using the variety Wuxiangjing14.Three nitrogen rates were 130 (N5), 260 (N6), and 390 (N7) kg·hm^{-2}. Sowing data was May 20th, transplanting data was June 20th and planting spacing 15 cm×25 cm. The fertilization of P and K and the other management measures followed common standard in local production. The experiment plots were arranged in three replications with the plot size of 31.5 m^2 (3.5 m×9.0 m) area.

2.1.2 Measurements of canopy spectral reflectance

Rice canopy reflectance spectral measurements during experiment 1 were made using a Field Spec Pro FR spectroradiometer (Analytical Spectral Devices, Boulder, GO, USA) over the 350 nm—2500 nm range with 3 nm (for the first spectrometer) and 10 nm (for the 2nd and 3rd spectrometers) resolutions on main growth stage (jointing, booting, heading and grain filling), respectively. The instrument with a 25°field of view and 100cm distance above rice canopy was used to collect spectral reflectance. All spectral measurements were made on cloudless clear days at mid-day, 10: 00—14: 00. The spectral measurements were taken at each plot as the average of five scans. The spectral data were compared to a white $BaSO_4$ reference, taken before the start of each spectral measurement, for calibration.

2.1.3 Remote sensing retrieval for agriculture parameter

Retrieval for leaf area index and leaf nitrogen accumulation were based on difference vegetation index of 854 nm and 760 nm [DVI (854,760)] and ratio vegetation index of 827 nm and 742 nm [RVI (827,742)] to estimate (Tian, 2008), and the estimated model was:

$$\mathrm{LAI} = 67.433 \times \mathrm{DVI}\,(854,760) + 0.1008 \tag{1}$$

$$\mathrm{LNA} = 24.424 \times \mathrm{RVI}\,(827,742) - 26.55 \tag{2}$$

2.2 Data utility and analysis

Data from experiment 1 was used for testing the accuracy in application of the technique we established in this article. Data from experiment 2 was used to further test the reliability of assimilation techniques. We used relative error (RE) and root mean square error (RMSE) of simulated value and true value to evaluate assimilation reliability.

3 SELECTION OF OPTIMIZATION ALGORITHM AND MODEL

3.1 Particle swarm optimization

Particle swarm optimization (PSO) was first proposed by Kennedy and Eberhart, and it groups each individual as a particle (point) with certain speed of flight and without quality and size in multidimensional search space. Every particle would modify their movement direction and speed through counting the optimal value in individual and group in iterative process, to form the positive feedback mechanism of group optimizing, and each particle of the environment based on the fitness of the individual gradually moves to more excellent region, and eventually to find optimal solution. The location of particles represents the solution of the problem to be optimized, and the performance advantages and disadvantages of each particle depend on the fitness decided by objective function of optimization problem. Each particle's velocity vector determines its direction and velocity of flight. Assuming there is a group(Swarm) consisting of m particles in D-dimensional search space with a certain speed flight, each particle in the search, considering the best search point in the history and other's in populations (or neighborhood) would change their location (state, another word is solution). Then:

The ith particle position is expressed as: $x_i=(x_{i1}, x_{i2},..., x_{id})$, $1\leqslant i\leqslant m$, $1\leqslant d\leqslant D$;

The ith particle velocity is expressed as: $v_i=(v_{i1}, v_{i2}, ..., v_{id})$,

The ith particle's best point in history is experienced as: $p_i=(p_{i1}, p_{i2}, ..., p_{id})$;

The best point of all particles in populations (or areas) is expressed as: $p_g=(p_{g1}, p_{g2},..., p_{gd})$.

In general, the particle position and velocity are continuous true values within the space. Particle position and velocity change according to the following equation:

$$v_{id}^{k+1}=v_{id}^{k}+c_1\xi(p_{id}^{k}-x_{id}^{k})+c_2\eta(p_{gd}^{k}-x_{id}^{k}) \tag{3}$$

$$x_{id}^{k+1}=x_{id}^{k}+v_{id}^{k+1} \tag{4}$$

Among the equation, c1 and c2 are the learning factor (Learning Factor) or acceleration coefficient which could give the ability of self-summary and learning from other outstanding particle to individual, then close to the best in their own history and neighbor area history. C1 and c2 values are usually 2 (Guo, *et al*., 2007). ξ and η∈U [0,1] and is a random number between 0 and 1. In order to prevent the particles far from the search space, particles flying speed is limited between a maximum speed $[-V_{\max}, V_{\max}]$, $V_{\max}$ is a constant, and in this study, the value is 10.

In the actual course of the study, dimension is the number of inversion parameters, and in this study is 3 and this algorithm is used in the process of minimizing grown information difference between remote sensing and growth model.

3.2 Rice grow model (RiceGrow)

In this study, the rice grow model (RiceGrow) we used was built in the lab in which author studied. RiceGrow (Meng *et al*., 2000, 2003, 2004) for the first time used physiological development time (PDT) as a quantitative measure of rice development process, and through introducing species-specific genetic parameters, we established the rice growth stage of development and the phenophase simulation sub-model based on physiological and ecological processes of the rice growth. Rooted on the foundation of quantitative analysis of dry matter production and distribution index of physiological development time and the dynamic changes of environmental factors, we constructed the model of dry matter accumulation and distribution and sub-model of organs and yield based on the partitioning index and photosynthesis. At the same time, we also combined the sub-model of soil-plant water balance and nutrient balance of the dynamic simulation. (Hu *et al*., 2004; Zhuang, *et al*., 2004).

The model system shows a good mechanism and predictability and could quantitatively describe and predict the quality of rice growth and yield formation of the dynamic process. Fig. 1 shows the rice growth model (RiceGrow) chart, the combination point with remote sensing is LAI and leaf nitrogen accumulation (LNA) from model output, and the assimilated parameters of model were the sowing date, seeding rate and nitrogen rate.

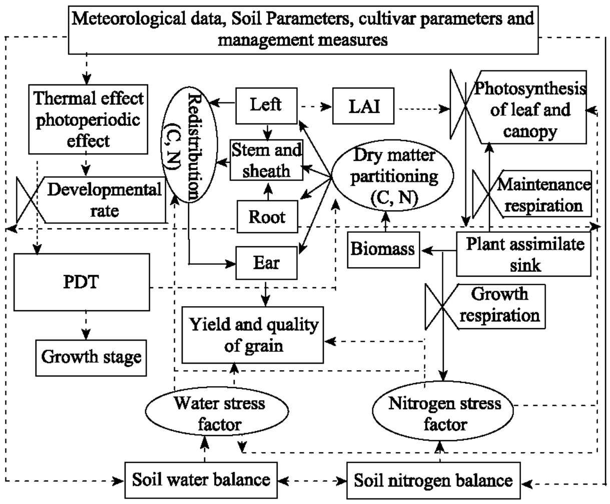

Fig. 1 Modular structure of RiceGrow model

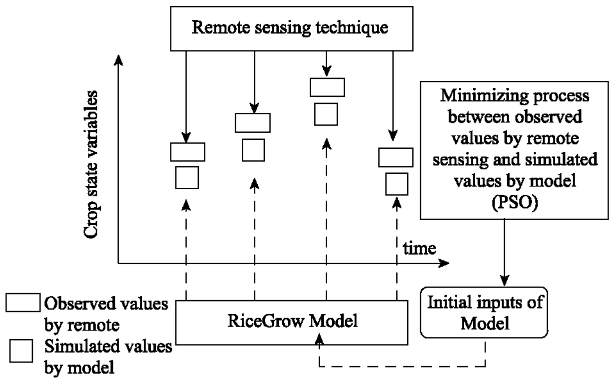

Fig. 2 Assimilation scheme of remote sensing and RiceGrow model

4 TECHNOLOGY OF ASSIMILATION REMOTE SENSING WITH MODEL BASED ON PSO

4.1 Assimilation of Remote Sensing Data with Crop Growth Model

The study used assimilation method to achieve the combination of remote sensing information and RiceGrow model. Through assimilating the state variables (LAI, LNA *et al.*) estimated by remote sensing, we minimized the difference between parameters which were estimated by remote sensing and corresponding parameter got from RiceGrow model. In this process, using PSO optimization, we constantly adjusted the initial parameter values of RiceGrow (sowing time, seeding rate and nitrogen rate) with higher assimilation speed. When initiating the input parameter of RiceGrow, we keep the prediction value from model and the simultaneous estimated value from remote sensing keeping converging until the difference is minimal. Then, we take the initial parameter after adjusted as the initial input parameter of crop growth model, and run RiceGrow (Fig. 2) to get more accurately predicted value of growth dynamic process and the yield and quality of rice.

When running crop growth model on spatial multi-points or region scale, the cultivation management parameters that model needs have large spatial variability in a certain region including sowing time, seeding rate and nitrogen rate. It is difficult to obtain these parameters sensitive to model on region scale, so we determine these three parameters as initial parameters to retrieve. Other initial parameter such as climatologically data, soil date and so on, could be acquired from data interpolation or relevant agencies. In addition, the previous studies always used LAI as the assimilation variable (Mass, 1998; Yang *et al*., 2009) and few used LNA physiological parameters as assimilation variable. However, LNA has remarkable theoretical signifycance to nitrogen diagnosis of crop, and it is directly bound up with crop yield (Feng, 2008). At the same time, LNA could be retrieved by remote sensing successfully (Zhu *et al*., 2006, Zhou. 2006).Therefore, LAI and LNA were chosen as junction of remote sensing and crop model, and a contrastive analysis was conducted in this study.

During the assimilation process, through comparing the LAI (LNA) sequence estimated by remote sensing with the LAI (LNA) sequence simulated by RiceGrow and computing with PSO optimization, the parameter (optimum parameters retrieved) including the initial sowing time, planting density, nitrogen rate at the time of the minimal absolute sum of the two sequence' remainder are confirmed as the initial parameter of the model, and the specific process of retrievals is seen in Fig.3. First, a group of model initial parameter is roughly given, the model is run to simulate a sequence of LAI(LNA) , which is compared with the LAI(LNA) sequence of correspondent time(date) estimated by remote sensing. Then, whether the difference of the two sequences is minimal is judged, and if it is, those are the optimal parameters; if not, keep adjusting initial parameter until the objective function value reaches minimal value. When applying at the region scale, through getting LAI(LNA) information at multi-point, and using the assimilation method mentioned above, initial parameters model needed could be retrieved, and the model special application could be extended from single point to region.

Objective function is defined as follows.

$$y=\frac{1}{n}\sum_{i=t}^{n}(|P_{\text{obvi}}-P_{\text{simi}}|) \quad (5)$$

where n is the number of external data assimilation, P is assimilation parameters (LAI or LNA in this article)

4.2 Correctness verification of assimilation technique

The feasibility of the assimilation technology based on PSO

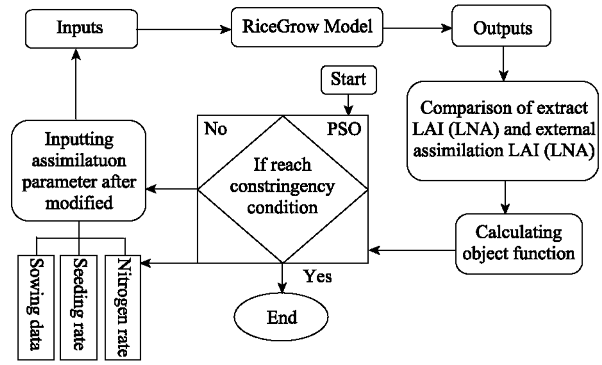

Fig. 3 Flow chart of assimilation process of remote sensing and model based on PSO

can be tested by verifying whether this assimilation technology could retrieve the initial parameters which input to running model forward when the parameters simulated from running model forward are used as external assimilation data. If it could, the assimilation technique was reliable. Took LAI for example, first give a group of parameter as real value, such as sowing date (May 15th), seeding rate (75 kg·hm^{-2}), nitrogen rate (250 kg·hm^{-2}). And then run RiceGrow model to simulate the daily production of LAI sequence, pick some of them an external assimilation LAI, and run assimilation techniques based on the proposed establishment RS-RiceGrow assimilation model to test whether the model can show the correct initial parameter information. The results showed that after running model 10 times, the RMSE between three initial parameter's retrieved values and their actual value were 0.7, 1.34, 2.2, and 3 average retrieved value is May 15th, 74.75 kg·hm^{-2} and 252.6 kg·hm^{-2},respectively. With the high precision, it was considered that the assimilation technique we established was correct. Meanwhile, a comparison between PSO and SA was made for the assimilation effect (Table 1), and also compared was run time the two algorithms spent. The results showed that the RMSE values between retrieval of sowing time, sowing rate and nitrogen rate value with SA and their actual values were 1.1, 1.64, and 2.81. From the time required to achieve target accuracy, we found that PSO took only one minute sixteen seconds, while the SA took seven minutes, which showed that the former is better than the latter in either retrieval accuracy or assimilation efficiency,. In addition, we also used LNA as external assimilation index: the RMSE were 1.3, 1.7, 1.095, the average value of retrieval sowing date was May 16th, and retrieval seeding rate was 76.9 kg·hm^{-2} and the retrieval nitrogen rate was 250.9 kg·hm^{-2}. It indicated that LAI and LNA

Table 1 Retrieved average results based on simulated LAI/LNA as external assimilation data

	Retrieved sowing date		Retrieved seeding rate/(kg·hm^{-2})		Retrieved N rate/(kg·hm^{-2})	
	LAI	LNA	LAI	LNA	LAI	LNA
SA	May 15th	May 13th	78	79.2	147.2	195
PSO	May 15th	May 16th	74.75	76.9	252.6	250.9

each had advantage as external assimilation parameters: sowing date and seeding rate could be well retrieved when LAI was selected as external assimilation parameter, while nitrogen rate was better predicted by using LNA.

4.3 Example analysis of assimilation technique

Based on date of soil, meteorology, variety and management measures, we analyzed the RS-RiceGrow assimilation model and the technique for getting initial inputs parameters under real situation. With LAI from assimilating remote sensing data and running RS-RiceGrow assimilation model to get sowing time, sowing rate and nitrogen rate, the result also showed that sowing date, seeding rate could be well retrieved when LAI was selected as external assimilation parameter, while nitrogen rate was better predicted using LNA. However, there is a big difference between the true value and the retrieval value of sowing time and sowing rate when using LNA as external assimilation parameter and the nitrogen rate's relative error is less than 2.5% using LAI as external assimilation, which was acceptable; hence, it is suggested that LAI is more suitable for this assimilation technique when using one external assimilation. Fig.4 to Fig.6 shows the result of inversion values of sowing time, sowing rate and nitrogen rate using LAI as external assimilation parameter. The simulated yield from assimilation model was shown in Fig.7. The results show that the retrieved values of three initial parameters are in agreement with the actual situation; the yield simulated from assimilation model bears about 5% error compared with real grain yield, which is also acceptable. Fig.8, Fig.9 and Fig.10 show the comparison difference of the data assimilation from models simulated, RiceGrow simulated and actual measured value based on experiment 2. From the figures, the various indicators from assimilation model are in good agreement with measured values, which further proves that this assimilation technique is accurate and reliable.

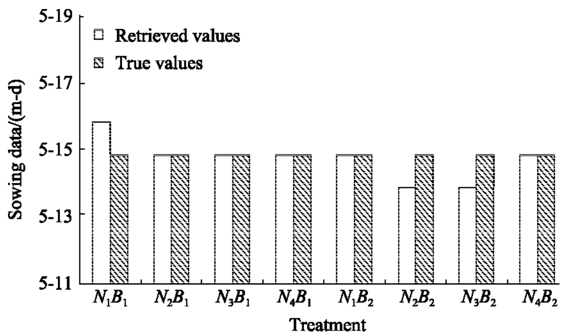

Fig. 4 Comparison of retrieved and observed sowing data

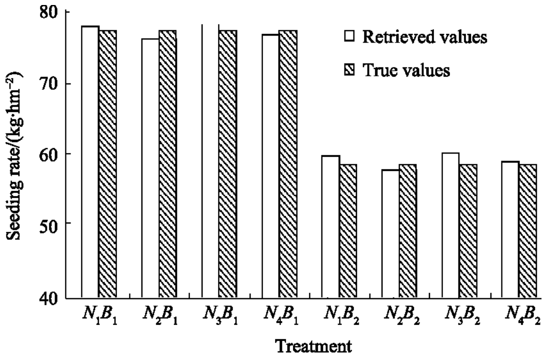

Fig. 5 Comparison of retrieved and observed seeding rate

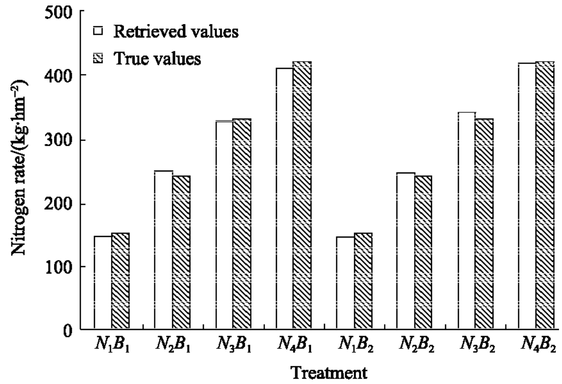

Fig. 6 Comparison of retrieved and observed nitrogen rate

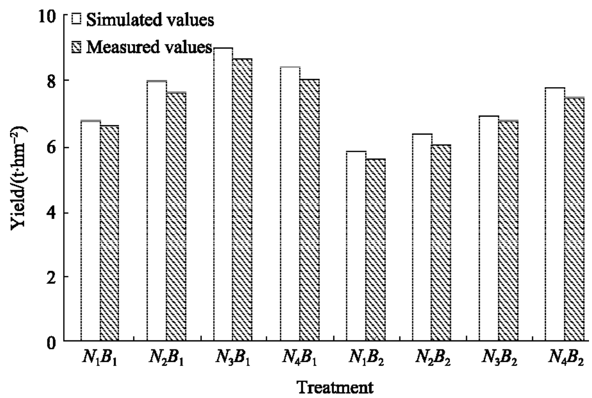

Fig. 7 Comparison of simulated and measured yield

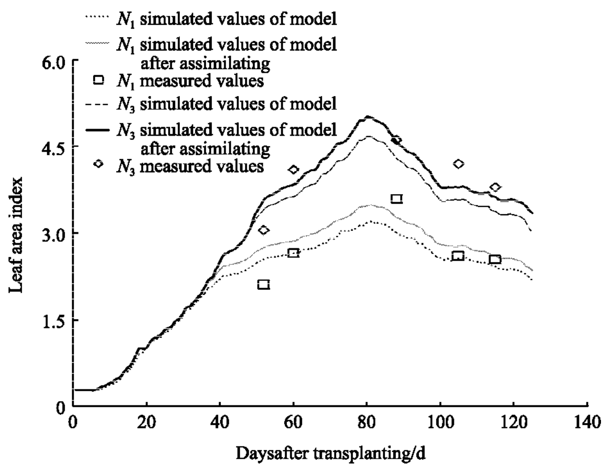

Fig. 8 Simulated LAI values by RS-RiceGrow assimilation model

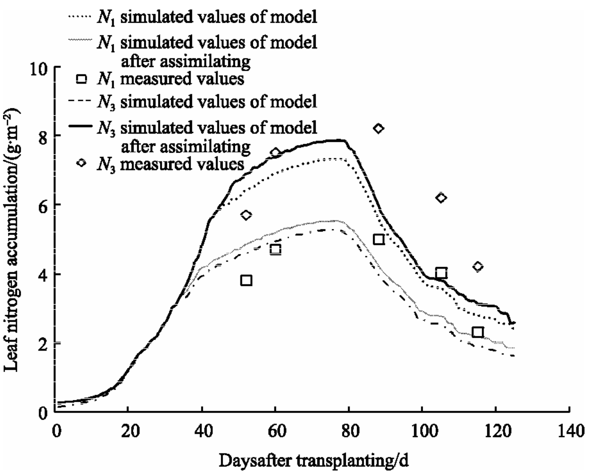

Fig. 9 Simulated LNA values by RS-RiceGrow assimilation model

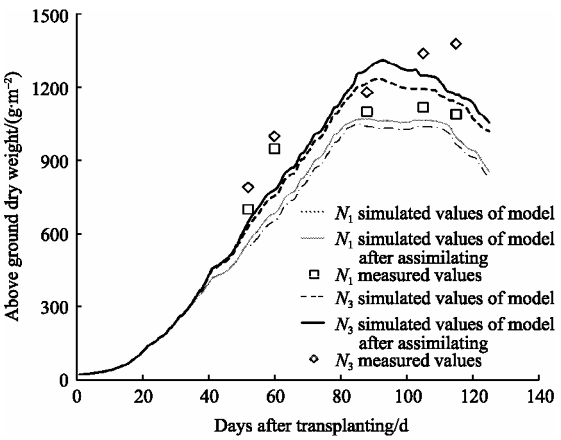

Fig. 10 Simulated above ground dry weight values by RS-RiceGrow assimilation model

5 DISCUSSION

Existing research shows that the choice of optimization method is very important in assimilation process of crop growth model and remote sensing data due to its effect on running efficiency and resultant accuracy of assimilation. In this study, a new optimization--Particle Swarm Optimization (PSO) was used for assimilating remote sensing data and RiceGrow model. PSO was compared with another optimization--Simulated Annealing (SA) and the result indicates that PSO is better than SA in both assimilation efficiency and retrieved accuracy. With retrieved nitrogen as an example, seven minutes is needed by SA but only one minute and thirty-six seconds by PSO to complete the assimilation process, and the retrieved accuracy of PSO is better than that of SA. On the other hand, PSO is simple in principle and easy to program. And there is extensive space for further improvement for ideal application (Gu *et al*., 2009; Chen *et al*., 2009). Therefore, this study suggests that the PSO has good prospect in the assimilation process of remote sensing information and crop growth model.

Currently, most studies used LAI as external variable of remote sensing and model assimilation (Maas, 1998; Yang, 2009), because the LAI product based on remote sensing is reliable and the study of remote sensing retrieved LAI is successful. And at the same time, LAI is one of the most important state variables of growth model. And there are few studies employing physiological data as external assimilation variable. In the choice of external assimilation parameter in this study, besides LAI, we used LNA which is an equally important physical index and conducted a comparative analysis of the results. The result shows that it is closer to the true value when LNA is used as external assimilation parameter for retrieved nitrogen and the same case is made for LAI for retrieved sowing and seeding, maybe because LNA is more sensitive than LAI in nitrogen module in RiceGrow model. At the next step of this study using both LAI and LNA as external assimilation parameter will be considered in order to improve the accuracy of the initial parameter inversion.

In the existing combination of optimization algorithm and model, the overseas growth model is always employed and the complicated optimization algorithm chosen. This study introduces a simple and effective algorithm-Particle Swarm Optimization and uses RiceGrow model which has independent intellectual property rights in collaboration with remote sensing information, and constructs an assimilation technique of remote sensing and RiceGrow model based on Particle Swarm Optimization. The test result shows that it has good application effect. It should be noted that a RiceGrow-remote sensing model assimilation technology built in the study is based on the accuracy and reliability of RiceGrow and remote sensing retrieved. So, how to improve the accuracy of RiceGrow model and remote sensing retrieved model in the assimilation process would be the key point in further study.

It should be also noted that the construction of assimilation technology by this study enables the model to be used in regional-scale, in short, the realization of model usage at any point of the area. Out of the limitation of altitude remote sensing information, this model is not credited with the application based on full remote sensing image. In the future, use more extensive ground and altitude remote sensing information should be used its testing and evaluation.

6 CONCLUSION

The assimilation technique of Remote Sensing information and RiceGrow model based on PSO is better than that based on SA in both assimilation efficiency and retrieved accuracy, which indicated that PSO is a reliable optimization algorithm for assimilating remote sensing information and model. Compared to LNA, the retrieved result is better when LAI is used as external assimilation parameter.

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应用粒子群算法的遥感信息与水稻生长模型同化技术

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摘　要： 在研究遥感信息和水稻生长模型的同化过程中，最小化遥感反演与生长模型(RiceGrow)输出的水稻生长信息差值绝对值时引入了一种新的优化算法-粒子群算法(PSO)，并对比了其与模拟退火算法(SA)的优缺点；探讨了叶面积指数(LAI)和叶片氮积累量(LNA)分别作为同化参数时的同化效果。结果表明，PSO 无论是从同化效率还是反演精度上都要好于 SA，粒子群优化算法是一种可靠的遥感与模型同化算法；LAI 和 LNA 作为外部同化参数时各有优势，LAI 作为同化参数可获得较准确的播期及播种量，而 LNA 作为同化参数可获得更为准确的施氮量信息。但是 LAI 作为外部同化参数时的反演结果总体要优于利用 LNA 作为同化参数时的反演结果。利用试验资料对该技术进行了测试和检验，结果显示反演的模型初始参数的平均值与真实值的相对误差(RE)均小于 2.5%，均方根误差(RMSE)为 0.7—2.2，产量模拟值与实测值之间的相对误差为 5%左右，模拟与实测相关指标值吻合度较高，该同化技术具有较好的适用性。从而为生长模型从单点扩展到区域尺度应用奠定了基础。

关键词： 粒子群算法，RiceGrow 模型，同化技术，模型参数初始化

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1　引　言

作物生长模型从作物生态系统物质和能量守恒及转换原理出发，应用数学物理方法定量描述了作物生理生态过程及其与外部环境条件的关系，是一种面向作物生长发育过程、机理性和时间动态性很强的过程模拟模型(宇振荣，1994)，它在单点水平上对叶面积指数、生物量和产量等具有较好的模拟预测精度(叶宏宝等，2007，2008)。作物生长模型运行时需要较多初始输入参数，包括气象、土壤、作物品种以及管理技术措施(如播期、密度、基肥施用量)等。当在多点或区域尺度应用作物生长模型时(如大面积估产)，这些初始参数在每个空间点上均有可能不同，从而导致了多点或区域尺度水平模型初始参数获取难的问题(刘布春等，2002)，进而限制了生长模型的大面积有效应用。因此，将可区域化应用的遥感技术与作物模型结合，成为作物模型区域化应用的关键技术。遥感可以为作物模型提供适时的环境参数，使模拟过程更加贴近实际情况，通过产量差分析，可为提高产量提供政策建议和方法指导(王纯枝等，2005)。此外，遥感还可为大面积作物生长参数信息的准确、实时获取提供有力工具(邓良基，2002；王人潮等，2002)，因此，将作物生长模型(时间过程连续)和遥感(空间尺度连续)这两个时空互补性强的技术进行有机结合，有望解决生长模型在空间多点或区域尺度应用时较难获取初始输入参数的科学问题(Wit 等，2007；Martin 等，2008)。

围绕作物生长模型与遥感技术的结合开展的研究包括：将遥感反演的参数作为作物模型的输入变量驱动模型运转的驱动法和利用遥感反演的状态变量校准作物模型的某些过程或重新初始化作物模型来优化模型的同化法(马玉平等，2005a)；基于同化

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方法的作物模型与遥感信息结合主要从作物模型、优化算法和待优化参数的选择、以及作物生长模型区域化方法等方面开展研究(马玉平等，2005b; Marie 等，2005)。研究表明，优化算法的选择在作物生长模型和遥感数据的同化中十分关键(闫岩，2006)，优化算法选择的成功与否，直接关系到同化的效率与反演结果的准确性。如赵艳霞等(2005)对复合形混合演化算法(SCE_UA)和模拟退火算法(SA)在遥感–棉花生长模型的同化中进行了应用，有效地进行了棉花产量的预测，产量的模拟误差在 5%左右; 闫岩等(2006)在遥感与 CERES_Wheat 模型的同化过程中采用了 SCE_UA 算法，取得了较好的效果。Guerif 和 Duke(1998)在遥感信息与 SUCROS 模型的同化过程中，采用 FSEOPT 优化程序获取了 SUCROS 模型运行所需要的一些重要参数(如播期，叶面积等)，较准确地预测了甜菜的产量。但上述几种优化算法原理较复杂，当需要自行编程对算法做出一定修改时有一定难度，这在一定程度上限制了它的应用。

本文旨在引入一种原理简单、易于耦合集成的优化算法—粒子群优化算法(PSO)(Kennedy 等，1995)，在水稻生长模型(RiceGrow)基础上，同化遥感反演的生长信息，从而建立水稻生长模型初始化参数的同化反演技术，研究结果有助于实现水稻生长模型在多点或区域尺度的运行和应用。

2 数据资料获取

2.1 试验设计与资料获取

2.1.1 试验设计

研究数据资料来自 2 个水稻田间试验，涉及到不同年份、不同品种类型、不同施氮水平和密度处理，具体试验设计如下:

试验 **1:** 2008 年在南京农业大学江浦农场进行。供试品种为盐粳 9 号，设 4 个施氮水平: 150(N_1)、240(N_2)、330(N_3)、420(N_4) kg·hm^{-2}，两个密度处理: D_1(株行距为 20×25 cm)，D_2(株行距为 30×25 cm)，共 8 个处理，重复 2 次，随机区组排列，5 月 15 日播种，6 月 15 日移栽。试验区氮肥基追比为 5　5，即基肥∶促花肥∶保花肥为 5　2.5　2.5，所有小区均配施 P_2O_5 为 55 kg·hm^{-2}，K_2O 为 60 kg·hm^{-2}，做基肥一次施用。小区面积(长×宽): 45 m×90 m，其他管理同当地水稻高产栽培。

试验 **2:** 2007 年在南京市农林局江宁实验区进行，供试品种为武香粳 14。设 3 个施氮水平，130 (N_5)、260(N_6)、390(N_7) kg·hm^{-2}。小区面积 31.5 m^2(3.5 m×9.0 m)，随机区组排列，3 次重复，5 月 20 日播种，6 月 20 日移栽，株行距为 15×25 cm。氮肥按基肥 35%、蘖肥 15%、促花肥 25%、保花肥 25%施入。全区配施 P_2O_5 135 kg·hm^{-2}，K_2O 190 kg·hm^{-2}，做基肥一次施用，其他管理同当地水稻高产栽培。

2.1.2 冠层高光谱获取

采用美国 Analytical Spectral Device(ASD)(2003)公司生产的 FieldSpec Pro FR2500 型背挂式野外高光谱辐射仪。波段范围为 350 nm—2500 nm，其中 350 nm—1000 nm 光谱采样间隔为 1.4 nm，光谱分辨率为 3 nm; 1000 nm—2500 nm 光谱采样间隔为 2 nm，光谱分辨率为 10 nm。在主要生育时期(拔节期、孕穗期、抽穗期、灌浆期)进行冠层光谱测定。测定选择在天气晴朗、无风或风速很小时进行，时间范围为 10:00—14:00，测量时探头距冠层垂直高度 1 m，视场角 25°，每次采集目标光谱前后都进行参考板校正，在视场范围内重复 5 次取平均值，每小区重复测量 5 个视场，取平均值作为该小区的光谱测量值。

2.1.3 农学参数的遥感反演

水稻各生育期的叶面积指数和叶片氮积累量的反演分别采用基于 854 nm 与 760 nm 的差值植被指数[DVI(854,760)]和基于 827 nm 与 742 nm 的比值植被指数[RVI(827,742)]进行估算(田永超，2008)，估算模型分别为:

$$\mathrm{LAI}=67.433\times\mathrm{DVI}(854,760)+0.1 \tag{1}$$

$$\mathrm{LNA}=24.424\times\mathrm{RVI}(827,742)-26.55 \tag{2}$$

2.2 数据利用与分析

试验 1 数据用于检验所构建的遥感-模型同化技术在实际应用中的准确性，试验 2 数据用来进一步验证所构建的同化技术的可靠程度。同化技术的可靠性评价指标采用模拟值与真实值的相对误差(RE)及均方根误差(RMSE)来衡量。

3 优化算法及模型选择

3.1 粒子群算法

粒子群算法(PSO)最早由 Kennedy 和 Eberhart 提出，它将群体中的每一个个体视为多维搜索空间中的以一定速度飞行，没有质量和体积的粒子(点)，每一个粒子通过统计迭代过程中自身的最优值和群体的最优值来不断修正自己的运动方向和速度大小，从而形成群体寻优的正反馈机制，并依据每个粒子

对环境的适应度将个体逐步移到较优的区域, 并最终搜索、寻找到问题的最优解。粒子的位置表示待优化问题的解, 每个粒子性能的优劣程度取决于待优化问题的目标函数确定的适应值, 每个粒子由一个速度矢量决定其飞行方向和速率大小。如假设一个由 m 个粒子(Particle)组成的群体(Swarm)在 D 维搜索空间中以一定的速度飞行, 每个粒子在搜索时, 考虑搜索到的历史最好点和群体内(或邻域内)其他粒子的历史最好点, 在此基础上进行位置(状态, 也就是解)的变化。那么,

第 i 个粒子的位置表示为: $x_i=(x_{i1}, x_{i2}\cdots, x_{id})$, $1\leqslant i\leqslant m$, $1\leqslant d\leqslant D$;

第 i 个粒子的速度表示为: $v_i=(v_{i1}, v_{i2},\cdots, v_{id})$,

第 i 个粒子经历过的历史最好点表示为: $p_i=(p_{i1}, p_{i2},\cdots,p_{id})$;

群体内(或领域内)所有粒子所经过的最好点表示为: $p_g=(p_{g1}, p_{g2},\cdots, p_{gd})$。

一般来说, 粒子的位置和速度都是在连续的实数空间内进行取值。粒子的位置和速度根据如下方程进行变化:

$$v_{id}^{k+1} = v_{id}^{k} + c_1\xi(p_{id}^{k} - x_{id}^{k}) + c_2\eta(p_{gd}^{k} - x_{id}^{k}) \tag{3}$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{4}$$

式中, c_1 和 c_2 为学习因子(Learning Factor)或加速系数(Acceleration Coefficient), 一般为正常数。学习因子使粒子具有自我总结和向群体中优秀个体学习的能力, 从而向自己的历史最优点以及群体内或领域内的历史最优点靠近。c_1 和 c_2 通常取值为 2(郭建青等, 2007)。ξ 和 $\eta\in U[0, 1]$是在[0, 1]区间内均匀分布的随机数。为了防止粒子远离搜索空间, 粒子的飞行速度的被限制在一个最大速度[$-V_{\max}$, $V_{\max}$]之间, $V_{\max}$ 是常数, 限制速度的最大值, 本研究中, 这个值为 10。

在实际研究过程中, 维数为待反演参数的个数, 本研究中为 3, 在最小化遥感反演与模型输出的生长信息差值时使用了此优化算法。

3.2 水稻生长模型(RiceGrow)

采用作者所在实验室构建的水稻生长模拟模型(RiceGrow)。RiceGrow(孟亚利等, 2000, 2003, 2004)首次以生理发育时间(PDT)作为定量水稻发育进程的尺度, 通过引入品种特定的遗传参数, 构建了基于发育生理生态过程的水稻阶段发育与物候期模拟子模型; 在定量分析水稻干物质生产及分配指数随生理发育时间及环境因子动态变化规律的基础上, 构建了基于光合生产和分配指数的水稻干物质积累与分配模拟模型以及器官建成与产量形成模拟子模型。与此同时, 还建立了与生长模型结合的土壤-作物系统水分平衡和养分平衡的动态模拟子模型(胡继超等, 2004; 庄恒扬等, 2004)。整个模型系统表现出了较强的机理性和预测性, 可定量描述和预测水稻生长及产量品质形成的动态过程。图 1 显示水稻生长模型(RiceGrow)结构图, 其中与遥感的结合点为模型输出的 LAI 和叶片氮积累量(LNA), 同化的模型参数为管理措施中的播种期、播种量和施氮量等信息。

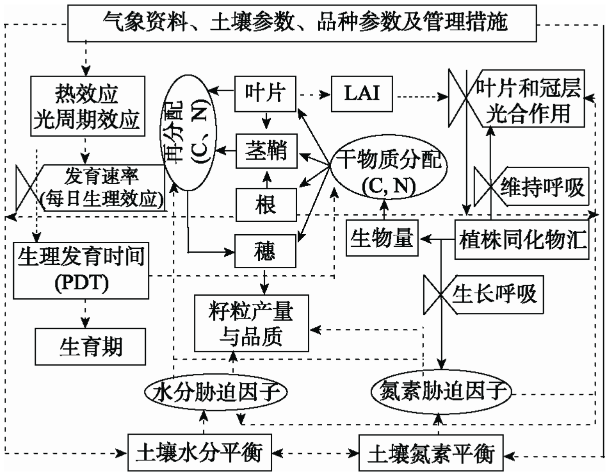

图 1 水稻生长模型(RiceGrow)结构图

4 基于 PSO 的遥感信息与模型同化技术

4.1 遥感信息与水稻生长模型(RiceGrow)的同化

采用同化法实现了遥感信息与水稻生长模型(RiceGrow)的结合。即通过同化遥感估测的状态变量(如 LAI, LNA 等), 最小化遥感估测的参数(如 LAI)与 RiceGrow 模拟输出的对应参数值差值的绝对值, 在此过程中, 引入 PSO 优化算法, 在提高同化速度的同时不断地调整 RiceGrow 初始参数值(如播种期、播种量和施氮量等), 对 RiceGrow 的输入参数进行初始化, 使得模型预测值与同时间的遥感估测值不断收敛, 直至相差最小, 然后将调整后的初始参数值作为作物生长模型的初始值和参数(图 2), 进而运行 RiceGrow, 模拟得到较为准确的水稻生长动态过程和产量品质的预测值。

空间多点或区域尺度运行作物生长模型时, 播种期、播种量、施氮量等 3 个模型需要的栽培管理措施参数在一定的区域范围内其空间变异相对较大,

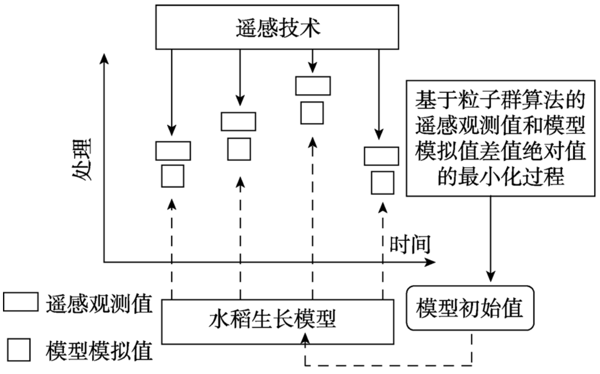

图 2 遥感信息与水稻生长模型(RiceGrow)同化示意图

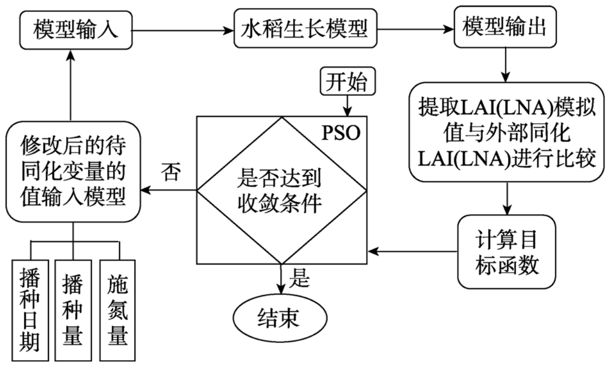

图 3 基于 PSO 的遥感模型同化过程示意图

模型比较敏感，而且通常在区域尺度上不易准确获取，因而将这 3 个参数确定为待反演的目标初始参数指标，而对于有些初始参数如气象资料、土壤数据等，可通过数据资料插值或相关机构的统计资料获得。另外，以往研究多以 LAI 作为模型的同化变量(Maas, 1998; Yang 等, 2009)，而较少利用 LNA 等生理参数作为同化变量。LNA 对作物群体氮素诊断具有重要理论意义，且与作物产量密切相关(冯伟等, 2008)，同时，遥感反演 LNA 也获得了成功(朱艳等, 2006; 周冬琴等, 2006)。因此，本研究选取 LAI 和 LNA 作为遥感和作物模型的结合点，并进行了对比分析。

同化过程中，通过对比遥感估测的 LAI(LNA)序列和 RiceGrow 模拟输出的 LAI(LNA)序列，经 PSO 优化算法计算，使两个序列差值绝对值之和(即目标函数)最小时的初始播种期、种植密度和施氮量等参数(即反演出来的最优参数)被确定为模型的初始参数，反演过程的具体流程见图 3。首先粗略给定一组模型初始参数，通过运算模型，模拟出一组 LAI(LNA)的序列，将其与遥感估测得到的对应时间(日期)的 LAI(LNA)序列进行比较，判断两组序列的差异是否最小，如果是，则该组参数为最优参数；否则，继续调整初始参数，直至目标函数值最小。这样，在区域尺度应用时，通过面上多点的遥感信息 LAI(LNA)，利用本文提出的同化方法即可反演出相应点上作物模型所需的初始参数，从而实现了模型由点到面的空间尺度扩展应用。其中优化目标函数定义为:

$$y=\frac{1}{n}\sum\nolimits_{i=t}^{n}(|P_{\mathrm{obvi}}-P_{\mathrm{simi}}|) \tag{5}$$

式中，n 为外部同化数据的个数，P 表示同化的参数(本文为 LAI 或 LNA)。

4.2 同化技术的正确性验证

检验基于 PSO 的同化技术是否可行，可看当以正向运行水稻模型得到的相关参数模拟值作为外部同化数据进行同化时，该同化技术是否能反演出正向模拟时给定的初始参数值，如果能，说明该同化技术是可靠的。以 LAI 为例，首先给定一组参数，作为真实值，如播种期(2007-05-15)、播种量(75 kg·hm^{-2})、施氮量(250 kg·hm^{-2})，然后运行 RiceGrow 模型，模拟产生逐日的 LAI 序列，取遥感反演的相应日期的 LAI 序列，将此 LAI 序列作为外部同化指标，运行基于本文提出的同化技术所建立的 RS-RiceGrow 同化模型，测试能否正确反演出生长模型的初始参数信息。结果表明，运行模型 10 次后，3 个待反演初始参数值与实际值之间的 RMSE 分别为 0.7, 1.34, 2.2, 3 个参数反演得到平均值分别是反演播期(2007-05-15)，反演播种量(74.75 kg·hm^{-2})，反演施氮量(252.6 kg·hm^{-2})，具有较高的精度，因此，可以认为本文建立的同化技术是正确的。同时，本文还对比了基于 PSO 和 SA 两种优化算法的同化效果(表 1)，并比较了两者同化运行时间。结果显示，使用 SA 反演的播期、播种量及施氮量值与实际值的 RMSE 分别为 1.1, 1.64, 2.81；从达到目标精度所需时间看，PSO 只需要 76 s，而 SA 需要 7 min，表明前者反演精度和同化效率好于后者。另外，以 LNA 为外部同化指标的同化结果是，RMSE 分别为 1.3, 1.7, 1.095，平均值为反演播期为 2007-05-16，反演播种量为 76.9 kg·hm^{-2}，而反演施氮量为 250.9 kg·hm^{-2}。与基于 LAI 为外部同化指标对比发现，利用 LAI 作为外部同化参数时反演的播期和播种量较准确，而利用 LNA 作为外部同化参数时反演的施氮量较准确。

4.3 同化技术的实例分析

利用试验 1 和试验 2 获取的真实土壤、气象、品种和栽培管理措施等数据，对构建的遥感与水稻生长模型耦合并进行模型输入参数初始化的技术进行了实例分析。通过同化遥感监测得到的LAI值，运

表 1　模拟 **LAI/LNA** 序列作为外部同化数据源的平均反演结果

	反演播种期		反演播种量/(kg·hm^{-2})		反演施氮量/(kg·hm^{-2})	
	LAI	LNA	LAI	LNA	LAI	LNA
SA	2007-05-15	2007-05-13	78	79.2	147.2	195
PSO	2007-05-15	2007-05-16	74.75	76.9	252.6	250.9

行 RS-RiceGrow 同化模型从而得到的播期、播种量和施氮量等初始化参数值, 反演结果显示 LAI 作为外部同化参数时反演的播期和播种量较准确, 而利用 LNA 作为外部同化参数时反演的施氮量较准确, 这与正确性验证结果一致。但是由于 LNA 作为外部同化参数时反演的播期与播种量与实际值相差较大, 而利用 LAI 反演的施氮量相对误差小于 2.5%, 可以接受。因此, 本研究认为以一个参数作为外部同化参数时, LAI 更适用。图 4—图 6 给出了 LAI 作为外部同化参数时模型反演的播期、播种量和施氮量结果, 同化模型模拟的产量如图 7。结果显示, 反演得到的 3 个初始参数与实际情况基本相符; 而同化模型模拟得到产量, 与实测产量存在 5%左右的误差, 也在可接受范围。

图 8—图 10 展示了基于试验 2 数据对比同化模型模拟值、RiceGrow 模拟值和实际测定值的差异, 从图中可以看出, 同化模型输出的各项指标值与实测值均较好的吻合, 从而更进一步证明所建立的同化技术是正确可靠的。

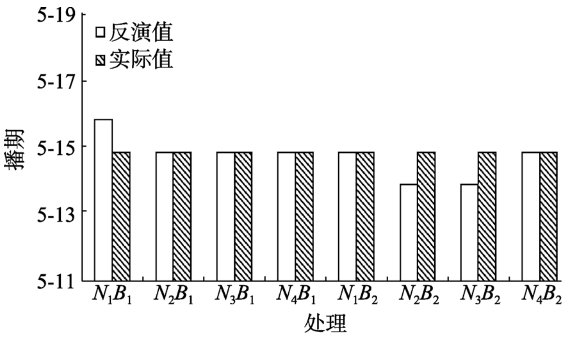

图 4　播期反演值与实际值比较

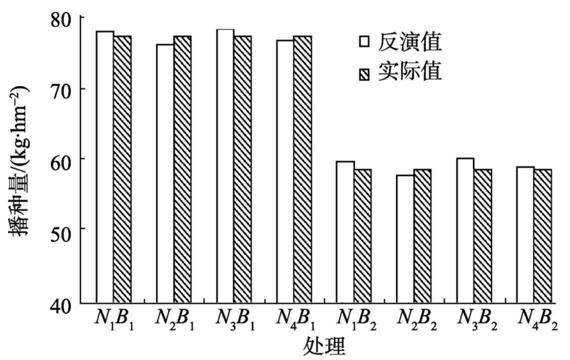

图 5　播种量反演值与实际值比较

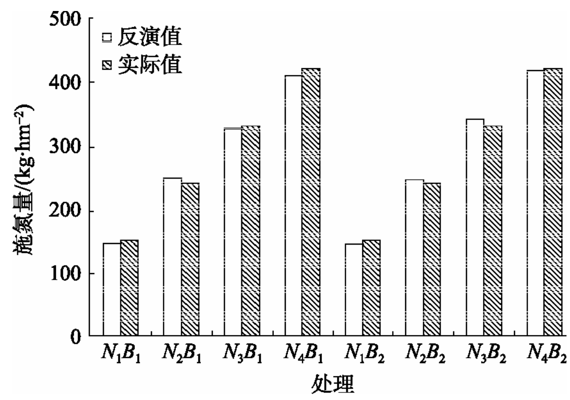

图 6　施氮量反演值与实际值比较

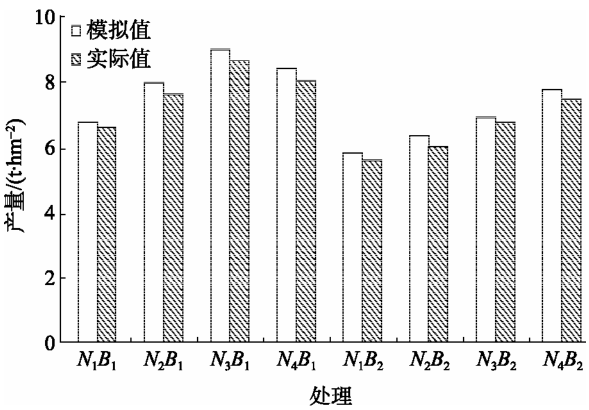

图 7　产量模拟值与实测值比较

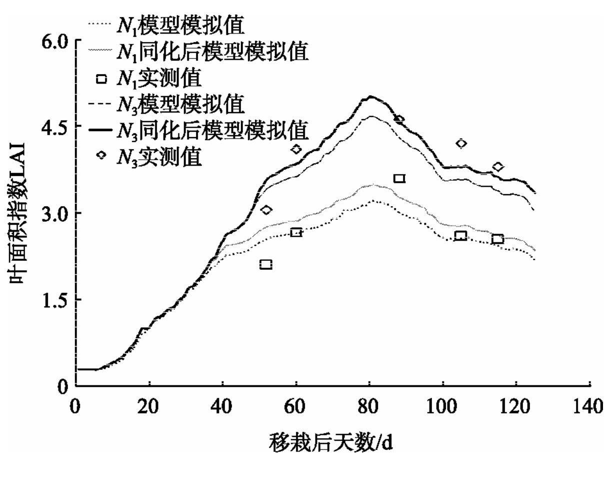

图 8　RS-RiceGrow 同化模型模拟的叶面积指数

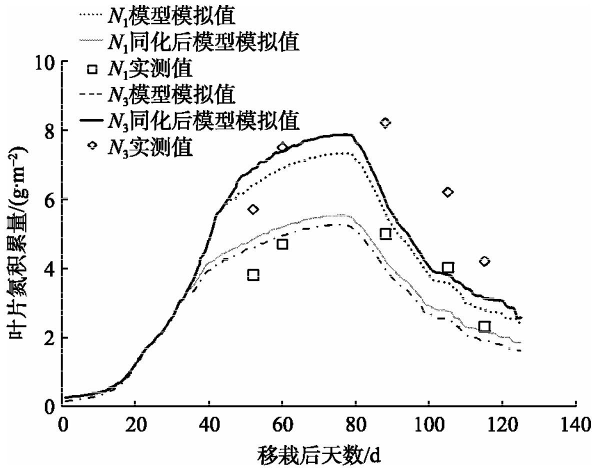

图 9 RS-RiceGrow 同化模型模拟的叶片氮积累量值

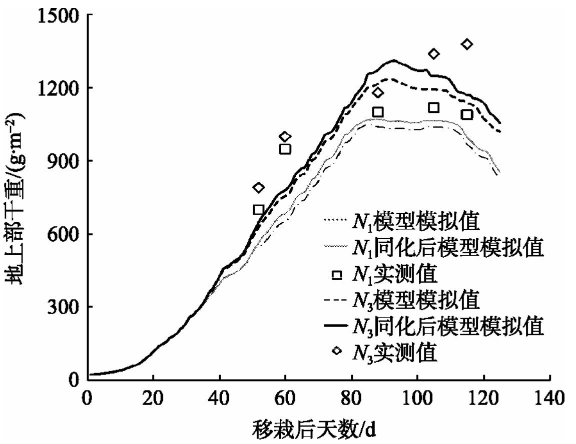

图 10 RS-RiceGrow 同化模型模拟的地上部干物重

5 讨 论

已有研究表明，优化算法的选择在作物生长模型和遥感数据的同化中起着十分重要的作用，优化算法选择的成功与否，直接关系到同化的效率与反演结果的准确性。本文在研究遥感信息和水稻生长模型的同化过程中，引入了一种新的优化算法-粒子群算法(PSO)，并对比了其与另一种优化算法(模拟退火算法 SA)的优缺点。结果表明，PSO 无论是从同化效率还是反演精度上都要好于 SA，以反演施氮量为例，使用 SA 时整个同化过程需要 7min，而使用 PSO 只需要 76s；而且 PSO 的反演的精度也要好于 SA 反演的结果。且 PSO 具有原理简单、易于编程实现的优点，可以达到更理想的效果和较广泛的应用(顾益磊等, 2009；陈炜等, 2009)。因此，本研究认为 PSO 优化算法在遥感信息与作物生长模型的同化过程中有良好的应用前景。

目前多数研究都采用 LAI 作为遥感与模型同化的外部变量(Maas，1998；Yang 等，2009)，主要原因是基于遥感的 LAI 产品具有良好的可靠性，遥感反演 LAI 的研究也较成功(王秀珍等, 2004；蒙继华等, 2007)，同时 LAI 是生长模型最重要的状态变量之一。而利用生理参数作为外部同化变量的相关研究还较少。本文在外部同化参数的选择上除了选用 LAI 外，还选用了同样较为重要的生理指标 LNA，并进行了结果对比分析。结果显示，本模型中利用 LNA 作为外部同化参数反演出的施氮量更接近真实值，而利用 LAI 作为外部同化参数反演出的播期与播种量更接近真实值。这可能是因为 LNA 对 RiceGrow 模型中的氮肥模块较 LAI 要更为敏感。因此本研究的下一步工作将会考虑同时使用 LAI 和 LNA 作为外部同化参数，以进一步提高初始参数反演的精度。

已有的优化算法和模型结合多采用国外生长模型，且采用的优化算法较为复杂(赵艳霞等, 2005；闫岩等, 2006)。首次引入简单有效的优化算法-粒子群算法，同时使用具有自主知识产权的水稻生长模型(RiceGrow)与遥感信息有效结合，初步实现了基于粒子群算法的遥感与水稻生长模型同化技术，测试结果表明本文方法具有良好的应用效果。需要指出的是，本文构建的遥感-生长模型同化技术的是建立在作物生长模型和遥感反演模型准确可靠的基础上的，因此，如何在同化过程中不断改善水稻生长模型和遥感反演模型的准确性是下一步研究的重点。

另外，本研究所建立的同化技术可使模型达到区域上的应用，指的是实现了模型在区域上任意一点上的应用，由于高空遥感资料有限，并没有将此模型做基于全遥感图像的应用，今后需要用更广泛的地面、高空遥感资料对其进行检验和评价。

6 结 论

基于粒子群优化算法(PSO)的遥感信息与水稻生长模型(RiceGrow)的同化技术在同化效率和反演精度上优于基于模拟退火算法(SA)的同化技术，表明粒子群优化算法是一种可靠的遥感与模型同化算法。同时，LAI 作为外部同化参数时的反演结果总体优于利用 LNA 作为同化参数时的反演结果，是一种良好的外部同化参数。

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