Spatial-time continuous changes simulation of crop growth parameters with multi-source remote sensing data and crop growth model

WU Ling, LIU Xiangnan, ZHOU Botian, LI Lufeng, TAN Zheng

School of information engineering, China University of geosciences, Beijing 100083, *China*

Abstract: Continuous simulation of crop growth parameters at spatial-time scale is a key technique for monitoring crop growth status and precision agriculture. This paper realized the spatial-time scale continuous simulation of growth parameters with the assimilation of remote sensing information into crop growth model, monitoring growth parameters changes on spatial-time scale. Construct a model named WOPROSAIL with the coupling of crop growth model WOFOST and canopy radiative transfer model Prospect+Sail (PROSAIL). Then particle swarm optimization (PSO) algorithm was used to minimize difference between observed values of soil adjusted vegetation index (SAVI) derived from CCD data and simulated values of soil adjusted vegetation index (SAVI') calculated by coupling model for optimizing initial parameters of WOFOST. Regionalization of parameters was achieved with MODIS data retrieval, then by inputting these regional parameters, optimized WOFOST model, initial parameters of which were optimized, was driven for each pixel and then regional growth parameters were calculated, achieving continuous simulation of crop growth parameters on spatial-time scale. Finally, a region scale remote sensing-crop simulation assimilation framework model named RS-WOPROSAIL was constructed. The results indicated that assimilation model solved the discontinuity of spatial scale simulation by crop growth model and time scale retrieval by remote sensing information. Growth parameters simulated by optimized crop growth model, including leaf area index (LAI), weight of storage organs (WSO) and total above ground production (TAGP), preferably reflected the changes of rice growth status on spatial-time scale, and the relative error between simulation yield and actual measurements was 27.4%.

Key words: crop growth model, PROSAIL model, particle swarm optimization algorithm, assimilation, crop growth parameters, spatial-time scale continuous simulation

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1 INTRODUCTION

Crop growth model's precision is high in simulating crop growth parameters such as leaf area index (LAI), weight of storage organs (WSO) and total above ground production (TAGP) on field scale which represent crop growth status (Wu, et al., 2003; Xie, et al., 2006), but when it is applied on region scale, some initial input parameters are unavailable due to the variability on region scale, limiting the application of crop growth model on region scale (Liu, et al., 2003). Therefore, the assimilation of remote sensing information into crop growth model becomes an effective approach to the regionalization application of crop growth model in recent years. On one hand, remote sensing technique can improve the simulation precision of crop growth model (Wang, et al., 2005). On the other hand, remote sensing technique can obtain input parameters on region scale accurately in real time (Wang & Huang, 2002). So combining remote sensing information with continuity on spatial scale and crop growth model with continuity on time scale is expected to realize the application of crop growth model on region scale, and accordingly the objective of the spatial-time scale continuous simulation of crop growth status can be achieved (Wit & Diepen, 2007).

At present, main studies about the assimilation of remote sensing technique and crop growth model include(1) adjusting some processes or re-estimating initial condition to optimize crop model with canopy state variable (LAI, LNA, et al.), which is acquired by remote sensing retrieval (Clevers, 1997; Yan, et al., 2006; Dente, et al., 2008; Zhu, et al., 2010; Tan, et al., 2011); (2)coupling crop growth model and canopy radiative transfer model with canopy state variable (LAI), and adjusting some processes or re-estimating initial condition to optimize crop model with remote sensing radiative observed values (Supit, 1997; Guerif &

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First author biography: WU Ling (1983—), male, Ph.D. candidate, he majors in the research of remote sensing information and process model coupling. E-mail: wl_19830807@sohu.com

Corresponding author biography: LIU Xiangnan (1964—), male, professor, his research interests are remote sensing information analysis and application of geosciences. E-mail: liuxncugb@163.com

Duke, 1998; Weiss, et al., 2001; Ma, et al., 2005). The first method demands high precision in the retrieval of the crop parameters with remote sensing. Comparing remote sensing radiative observed values with simulation ones by crop growth model, the second one adjusts some processes or re-estimates initial parameter(s), which does not introduce errors from the retrieval. So it becomes the important research direction.

In this study, the first step is to couple the crop growth model WOFOST and the canopy radiative transfer model PROSPECT+SAIL (PROSAIL). Second the particle swarm optimization algorithm (PSO) is used to assimilate soil adjusted vegetation index (SAVI) (Huete, 1988) derived from CCD data into the PROSAIL model to re-estimate some initial parameters of WOFOST for improving the simulation accuracy of WOFOST. Regionalization of parameters such as temperature (T) and photosynthetically active radiation (PAR) is achieved via remote sensing retrieval, by inputting which optimized WOFOST model was driven and then growth parameters were calculated on region scale. Finally, the regional scale remote sensing-crop simulation assimilation framework model (RS-WOPROSAIL) is constructed and is driven to simulate rice growth parameters on spatial-time scale continuously, providing reference for data modeling and analysis on spatial-time scale.

2 EXPERIENT AREAS AND DATA

2.1 Experiment areas

The Experiment region is located in the city of Changchun, Jinlin province (43°26′N—44°05′N, 125°03′E—125°34′E), which is in the north-east Plain of China. The climate is a cold temperate continental monsoon, abundant light and moderate heat. The annual average air temperature is 4.9℃ and the annual average precipitation is 594 mm, which mostly occurs and up to 311 mm in July and August; the soil is black earth mainly, property of which is fertile. The study region belongs to rice-growing area of single precocity rice in the north-east. The kind of rice is the series of Jilin japonica rice. In this study, four rice growth areas (A, B, C, D) and a sample plot(125°09′E, 43°51′N) were selected as study areas and sample plot respectively (Fig. 1).

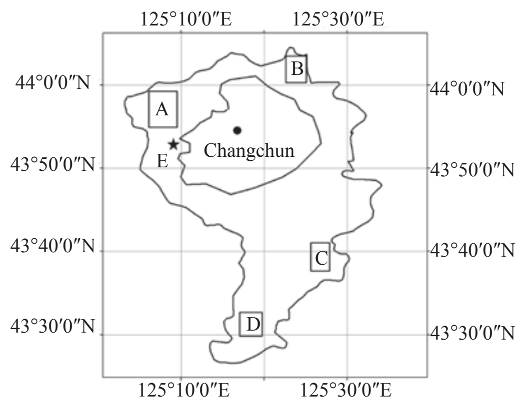


Fig. 1 Location map for study areas, sample plot and corresponding CCD data

2.2 Data acquisition

Data needed in this study included remote sensing data, WOFOST data, PROSAIL model and in situ observed data of rice.

Remote sensing data mainly used in the study was CCD data of the Environment and Disaster Reduction Small Satellites, which has the characteristics of high spatial resolution (30 m), high time resolution (four days) and large breadth (360 km or 720 km). 12 CCD data with good quality were selected from May to September in 2009 in this study, the time of which are 2009-05-20, 2009-06-20, 2009-06-25, 2009-07-08, 2009-07-19, 2009-07-29, 2009-08-04, 2009-08-12, 2009-08-30, 2009-09-04, 2009-09-10 and 2009-09-16, covering all growth periods of rice. With the calibration coefficient of each band provided by China Centre for Resources Satellite Data and Application, radiometric calibration of CCD data was conducted, and then geometric rectification with rectified TM image selected as base image and atmospheric correction based on 6S model were also carried out. In addition, three MODIS products such as MOD09 (the surface reflectance), MODIS-NDVI and Land Surface Temperature (LST) were selected for regionalization of parameters.

This study only performed the simulation of potential rice growth process, the parameters of WOFOST Principally included weather and crop parameters. And weather parameters included solar radiation and air temperature (T). Because the location of sample plot is close to that of Changchun weather station (125°13′E, 43°54′N), the daily air temperature data of Changchun in 2009 was selected as the air temperature data of sample plot from Changchun weather station. The solar radiation R_S was calculated by Eq. (1) (Doorenbos & Pruitt, 1977).

$$R_s = \left(a_s + b_s \frac{n}{N}\right) R_a \tag{1}$$

where a_s and b_s are empirical constants, the value of which are 0.25 and 0.5 respectively. n is the sunshine duration, acquired from Changchun weather station. N is duration of possible sunshine and R_a is extraterrestrial solarradiation.

Soil reflectance, contents of chlorophyll and dry mass as well as water of leaf in main periods required by PROSAIL and the crop growth parameters such as LAI, TAGP and WSO standing for rice growth status were also measured in sample plot. 40 sets of sample data were measured in every period, calculating the average of the 40 sets as the observed values of sample plot in each period.

3 ASSIMILATING OF REMOTE SENSING INFORMATION INTO CROP GROWTH MODEL

Construction of the assimilation framework was to construct a model named WOPROSAIL by coupling the crop growth model WOFOST under potential production level with the canopy radiative transfer model PROSAIL through LAI. Particle swarm optimization algorithm was used to minimize difference between simulated values SAVI’ by coupling model and observed values SAVI by CCD data for optimizing initial parameters. These variables include Day of Transplanting (IDTR) and temperature sum from sowing to transplanting (TSUMST) of WOFOST, which made simulated values close to observed ones. So the field scale remote sensing-crop simulation assimilation model was established; regionalization of parameters such as temperature (T)

and photosynthetically active radiation (PAR) was finished via MODIS data, by inputting which optimized WOFOST model was driven and then growth parameters (LAI, WSO and TAGP) were calculated for each pixel, and constructed a region scale remote sensing-crop simulation assimilation framework model named RS-WOPROSAIL. Finally, the study achieved continuous simulation of crop growth parameters on spatial-time scale.

3.1 Coupling of crop growth model and canopy radiative transfer model

The crop growth model WOFOST was used in this study, which principally simulates the processes including crop development, CO_2 assimilation, respiration, dry mass distribution, LAI increase and soil water balance as well as transpiration (Boogaard, et al., 1998). There are three simulation levels of crop growth: potential production level (suitable water and nutrient), water-limited production level (only rainfall) and nutrient-limited production level (Nitrogen, phosphorus and potassium short supplied). This study did research on the rice growth status under potential production level. Under potential production level, WOFOST determines crop development stage through calculating temperature SUM during crop growth stage. When the daily temperature sum accumulates to the total temperature sum needed for some development stage, it means crop has grown to the stage. Considering coefficient of the atmospheric transmission, direct and diffuse light, canopy reflectance, scattering and absorbability and so on, WOFOST describes the light interception of canopy, with which WOFOST calculates the potential gross photosynthate. Part of photosynthate are used to maintenance respiration and growth respiration, and the rest converts into dry mass and are partitioned to roots, stems and leaves as well as storage organs. The partition coefficients vary from one development stage to another and the gross weight of each organ is calculated by taking the integral of daily photosynthate. During the crop development process, leaves are grouped according to leaf age and age or dead with leaf age increasing, and influence the light interception (Fig. 2).

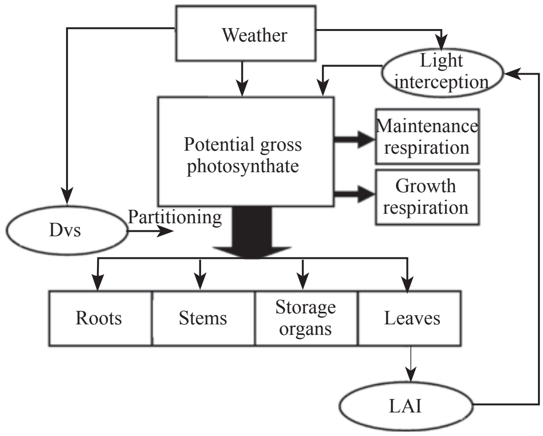


Fig. 2 Simplified structure of WOFOST under potential production level

PROSAIL model is in tegrated by PROSPECT and SAIL model. PROSPECT is a leaf optical properties model based on "Slab model" (Jacquemoud & Baret, 1990). It gets the reflectance and transmittance of leaf through simulating up and down radiant flux of leaf from 400 nm to 2500 nm. SAIL is a bidirectional canopy reflectance model (Verhoef, 1985), which LAI is one of input parameters. When canopy structure parameters and environment parameters are provided, SAIL model can calculate the canopy reflectance no matter how high the sun is and how the observation direction is oriented. PROSAIL model can get canopy reflectance of vegetation through inputting the leaf reflectance and transmittance simulated by PROSPECT into SAIL.

When physicochemical parameters of crop and weather parameters in the region are provided, WOPROSAIL could simulate canopy reflectance of vegetation through inputting LAI simulated by WOFOST into PROSAIL (Fig. 3). It comes true that the obtention canopy reflectance of vegetation according to vegetation physicochemical parameters and geometric parameters as well as weather parameters. This establishes the foundation for adjusting simulation processes or re-estimating initial parameters to optimize crop growth model with remote sensing radiative observed values.

3.2 Choice of optimization parameters

Cold damage is the primary climate factor of affecting the production of rice in Changchun, so the greenhouse are used to raise

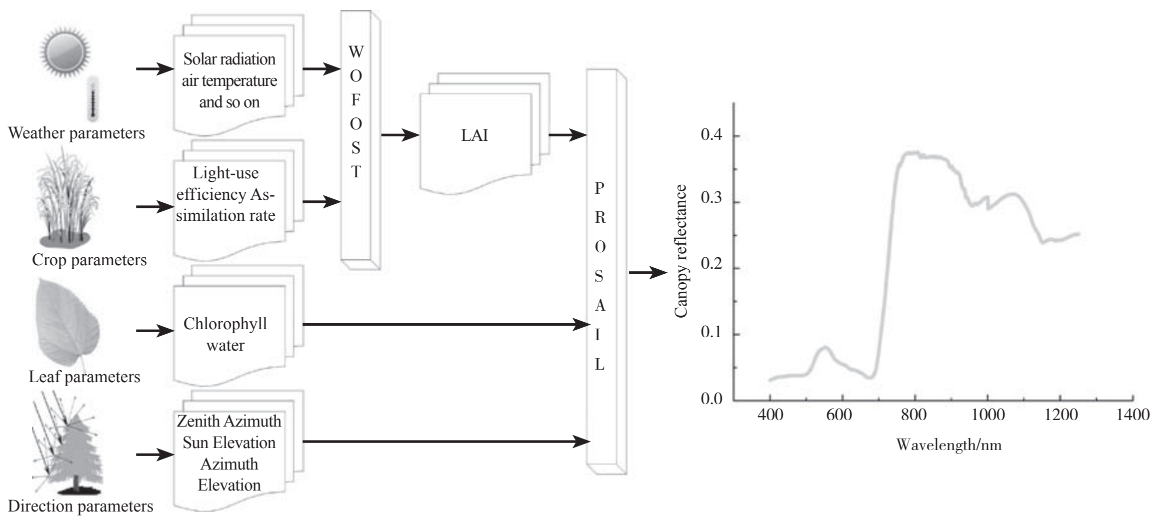


Fig. 3 WOPROSAIL coupling framework under potential production level

seeding in this region to increase the count of TSUMST for keeping rice grow in the right way. But TSUMST could not be acquired by remote sensing retrieval or spatial interpolation. Furthermore, it is very important for simulating the process of rice growth precisely. In addition, because of its variability on regional scale, IDTR is also unavailable on regional scale precisely.

With the sensitivity analysis, we tested impact of IDTR and TSUMST on simulation results, which means testing the changes in the percentages of simulation results (maximum LAI, final WSO and TAGP) with TSUMST reduced 10% (or setting IDTR ten days in advance or delay) when other parameters do not change anything (Table 1). It showed that maximum LAI reduced 11.39% and 10.57% respectively with setting IDTR ten days delay or TSUMST reduced 10%, which will influence photosynthesis. At the same time, the change range of final WSO and TAGP were also from 4.5% to 9.78% and from 6.1% to 9.09% severally, meaning that IDTR and TSUMST have large influence on crop development and biomass.

Table 1 Sensitivity analysis of IDTR and TSUMST /%

	IDTR		TSUMST reduced 10%
	Advance(10 d)	Delay(10 d)	
maximum LAI	7.85	−11.39	−10.57
final WSO	4.58	−9.78	−8.42
final TAGP	6.1	−9.09	−8.18

From above, the study determined IDTR and TSUMST, which are difficult to be acquired at regional scale precisely but have evident influence on simulation results, as the initial parameters to be optimized.

3.3 Regionalization of parameters

Considering the spatial non-homogeneity of surface condition, regionalization of parameters in the coupled model is required when a field scale model is applied on regional scale.

The model used in this study simulated rice growth under potential crop production, so it was principally influenced by PAR and *T*. To acquire space distribution of PAR, based on radiative transfer equation, we retrieved PAR with MODIS data whose time resolution is similar with the simulation step of WOFOST (Liu, et al., 2004); the results of *T* through spatial interpolation are influenced by the density and distribution characteristics of weather stations, and there is only one weather station in the study area, causing acquiring space distribution of *T* to be impossible. Since *T* is correlated with LST for dense vegetation, NDVI-Ts method was used to obtain the spatial distribution (Qi, et al., 2005).

Because rice in study area are mostly the series of Jilin japonica rice, the hereditary characteristics of which during growth period are general the same, so the crop parameters in model, including specific leaf area, net photosynthetic rate, distribution coefficients of day mass and so on, were set as uniform values according to observed data and some data in related articles (Wu, et al., 2009). Some parameters related to temperature, such as temperature sum from transplanting to anthesis (TSUM1), temperature sum from anthesis to mature (TSUM2), were acquire from space distribution in accordance with *T* calculated by the before-mentioned method. At the same time, accommodation of the WOFOST model was carried out to make it fit with simulation of rice growth in Changchun.

The spatial distribution of the leaf parameters in PROSAIL such as contents of leaf chlorophyll and water were retrieved with MODIS data based on green normalized difference vegetation index (GNDVI) (Gitelson, et al., 1996) and normalized difference water index (NDWI) (Gao, 1996) separately. Since soil in study area is mainly black soil, we used observed soil reflectance data as soil reflectance of canopy parameters. The spatial distribution of direction parameters, including solar zenith angle, view zenith angle, azimuth angle, were derived from CCD images. Other parameters, such as the content of day mass, carotenoid, brown pigment, mesophyll structure parameter, leaf angle distribution and fraction of direct incoming radiation as well as hot parameter, were set as fixed values based on observed or empirical values.

3.4 Optimization algorithm

Optimization is important to minimize difference between simulated values and observed values in the process of assimilating remote sensing data into crop growth model. The property of optimization algorithm and the dependence on priori knowledge influence the actual application of assimilated crop model in large part (Li, et al., 2008). In this study, an optimization algorithm with simple principle, which can be easily integrated into other models, was introduced-particle swarm optimization algorithm (PSO) (Kennedy & Eberhart, 1995). The basic idea is to group each individual as a particle (point) with certain speed of flight without quality and size in multidimensional search space. Every particle would modify their movement directions and speeds through counting the optimal value in individual and group in iterative process, forming the positive feedback mechanism of group optimizing. Based on the fitness to environment of the individual, each particle gradually moves to more excellent location, and eventually to find optimal solution. The location of particles is depended on cost function, whose input variables are the coordinate values of the particles' location.

In this study, the number of dimensions in multi-dimensional search space represented the number of optimization parameters (2). The number of particles represented groups containing two optimized parameters (25 groups), the values of which were random in the range. Once iteration happened, the random values changed, the iteration would not stop until cost function value was minimized. The maximum number of iteration was 400. If the cost function value did not change when the time of iteration exceeds 100, the iteration would stop.

3.5 Construction of remote sensing-crop simulation assimilation framework model on region scale

The study calculated SAVI' according to canopy reflectance simulated by coupled model WOPROSAIL, and then minimized the difference between SAVI' and SAVI gotten from CCD images. PSO algorithm was introduced in the process to continually adjust optimization parameters (IDTR and TSUMST) and then SAVI' simulated by WOPROSAIL was adjusted, making the difference between SAVI' and SAVI converge until minimization. Adjusted optimization parameters as the initial parameters of crop growth model and run WOFOST to obtain precise dynamic process of rice growth, and thereby a field scale remote sensing-crop simulation assimilation framework model named RS-WOPROSAIL was constructed (Fig. 4). The expressions of SAVI and the cost function are shown as below.

$$\text{SAVI}=\frac{\rho_{\text{nir}}-\rho_{\text{red}}}{\rho_{\text{nir}}+\rho_{\text{red}}+0.5}(1+0.5) \tag{2}$$

$$Q=\frac{1}{p}\sqrt{\sum_{i=1}^{i=p}(x_i-y_i)^2} \tag{3}$$

where ρ_{red} and ρ_{nir} represent the red band (the third band) and near-infrared band (the forth band) of CCD image respectively, Q is the value of const function, P is the number of external assimilated data, x_i is SAVI' at one point in time calculated by vegetation canopy reflectance simulated by WOPROSAIL, y_i is SAVI at one point in time calculated by CCD data.

With these regional parameters of crop, leaf and direction as well as climate, acquired in Section 3.3, field scale RS-WOPROSAIL model was driven for each pixel to acquire the space distribution of IDTR and TSUMST. With two optimized parameters and regional parameters of climate as well as crop parameters, WOFOST was driven for each pixel again, and a regional scale remote sensing-crop simulation assimilation framework model was established (Fig. 5).

4 ANALYSIS OF SIMULATION RESULTS

4.1 Continuous simulation of growth parameters on spatial and time scale

The regional scale RS-WOPROSAIL model achieved the objective of spatial-time scale continuous simulation of rice growth parameters, solving the discontinuity of spatial scale simulation by crop growth model and time scale retrieval by remote sensing information. Through bringing remote sensing information, the assimilation model can be scaled up. The retrieval of rice growth parameters with remote sensing information is influenced by cloud and rain as well as time resolution of remote sensing image. When remote sensing information is inaccurate, the precision of remote sensing retrieval is influenced. Assimilation model generally was not influenced by cloud and rain and the step-length is one day, avoiding the problem of blank such associated with remote sensing retrieval. Considering RS-WOPROSAIL established based on crop growth model and canopy radiative transfer model, its mechanism is stronger and the universality is higher compared with remote sensing statistics method. Therefore, the region scale RS-WOPROSAIL model could obtain the space distribution of rice growth parameters at any point in time (step-length is one day) during growth period (Fig. 6), and then we can estimate the rice growth status at anytime in study area, providing the useful information for agriculture production and management.

4.2 Change characteristics analysis of growth parameters on time scale

Before running the assimilation model, a group of initial optimization parameters were given different from observed datas, such as IDTR and TSUMST were set for Day 147 (2009-05-27) and 150℃ respectively. Then optimized IDTR and TSUMST were acquired through assimilating SAVI derived from CCD data into RS-WOPROSAIL (Table 2). The difference among

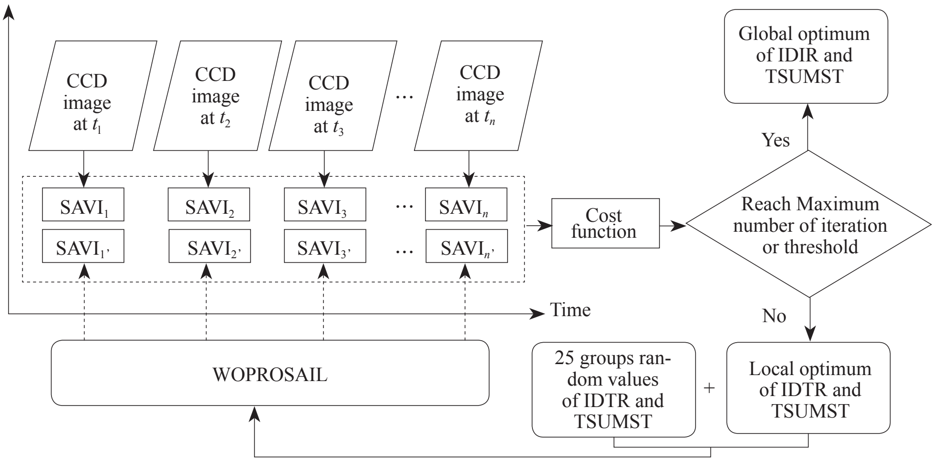


Fig. 4 Field scale RS-WOPROSAIL assimilation framework model based on PSO

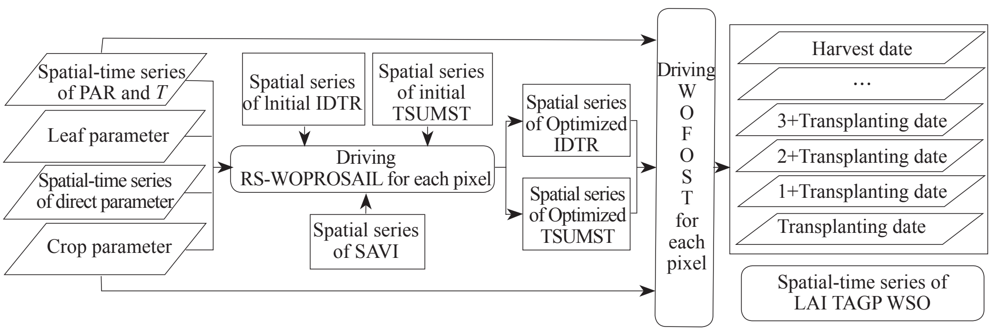
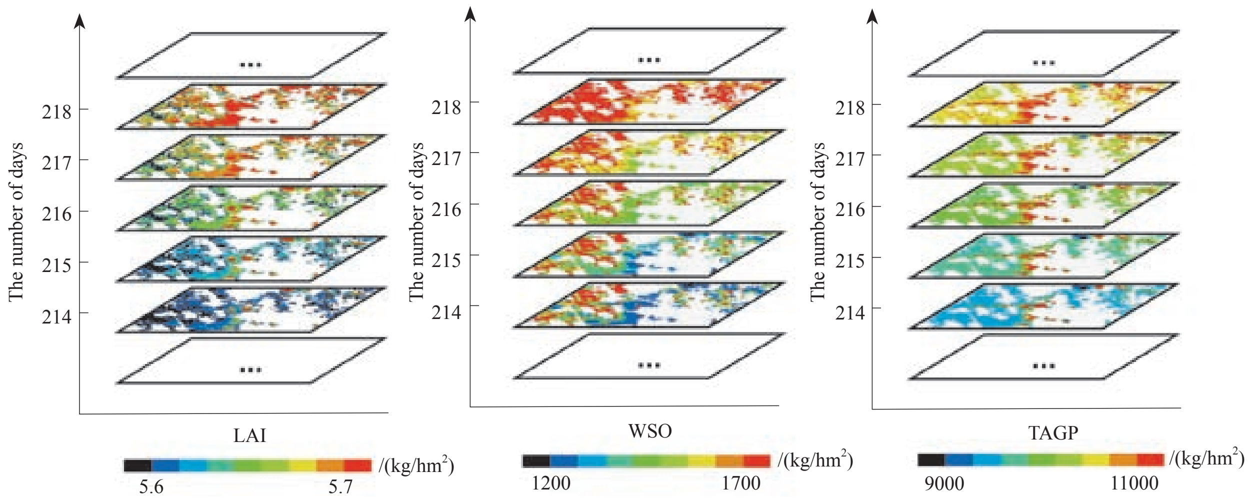


Fig. 5 Region scale RS-WOPROSAIL assimilation framework model



(a) Continuous simulation of LAI (b) Continuous simulation of WSO (c) Continuous simulation of TAGP

Fig. 6 Continuous simulation of LAI, WSO and TAGP of rice on spatial-time scale in study area A

optimized days and observed days including IDTR and day of anthesis (IDAN) as well as day of mature (IDMA) in sample plot were Two, three and four days, respectively. The difference between optimized TSUMST and observed TSUMST also decreased drastically.

Table 2 Optimized results of IDTR and TSUMST of rice

	TSUMST/℃	IDTR/days	IDAN/days	IDMA/days
Initial values	150	147	222	274
Optimized values	194	139	219	264
Observed values	225	137	216	260
Error between initial values and observed values	75	10	6	14
Error between initial values and observed Values	31	2	3	4

Simulated the process of rice growth with the optimized IDTR and TSUMST inputted WOFOST. Compared with the initial simulated values by WOFOST and observed values, the results of simulated rice LAI, WSO and TAGP by RS-WOPROSAIL were ameliorated, preferably reflecting that LAI and WSO as well as TAGP' change with the growth period (Fig. 7). The optimized values of LAI gradually increased after transplanting date (Day 139) until up to maximum value 5.76 at heading stage (Day 222). The optimized value of LAI gradually decreased (Fig. 7(a)) as rice growth enter the veproductive stage and rice leaves were on the aging process. After entering reproductive stage, the rice growth gave priority to the increase of storage organs, leading to accelerate the growth of WSO (Fig. 7(b)). At the late rice growth period, weight of stems (WST) and weight of leaves (WLV) gradually decreased as stems and leaf aging and dying gradually, but WSO gradually increased at the same time, so the optimized value of TAGP gradually increased during the rice growth period (Fig. 7(c)(d)). With assimilation of remote sensing information into crop model, the relative error between simulation yield (the final WSO) and actual yield was 18.8% instead of 33.6%, and the relative error between simulation final TAGP and actual one was 14.5% instead of 29.3% (Table 3). It demonstrated that the model RS-WOPROSAIL was reliable, which established the foundation for constructing a regional scale model.

4.3 Change characteristics analysis of growth parameters on spatial scale

Before simulating continuously crop growth parameters on spatial scale, RS-WOPROSAIL simulation framework model was driven to get the spatial distribution of IDTR and TSUMST. The distribution characteristic of optimized IDTR was IDTRD > IDTRC > IDTRB > IDTRA (Fig. 8). The reason was T in study region decreased gradually from northwest area to southeast area (Table 4), but it could transplant rice only when the average daily T kept above 13℃, so the IDTR of northwest area were earlier than that of southeast area.

To make rice grow in the right way, more TSUMST were needed through growing seeding in the greenhouse in the area where the IDTR of rice was a little late. It could solve the problem of impeding growth because of the low external temperature. The distribution of optimized IDTR was $TSUMST_D > TSUMST_C > TSUMST_B > TSUMST_A$ (Fig. 9).

Table 3 The optimized simulated results of rice yield and final TAGP

	Initial values/(kg/hm²)	Optimized values/(kg/hm²)	Observed values/(kg/hm²)	Error between initial valuer and observed valuer/%	Error between optimized valuer and observed valuer/%
Yield	12007	10678	8987	33.6	18.8
Final TAGP	21981	19465	16994	29.3	14.5

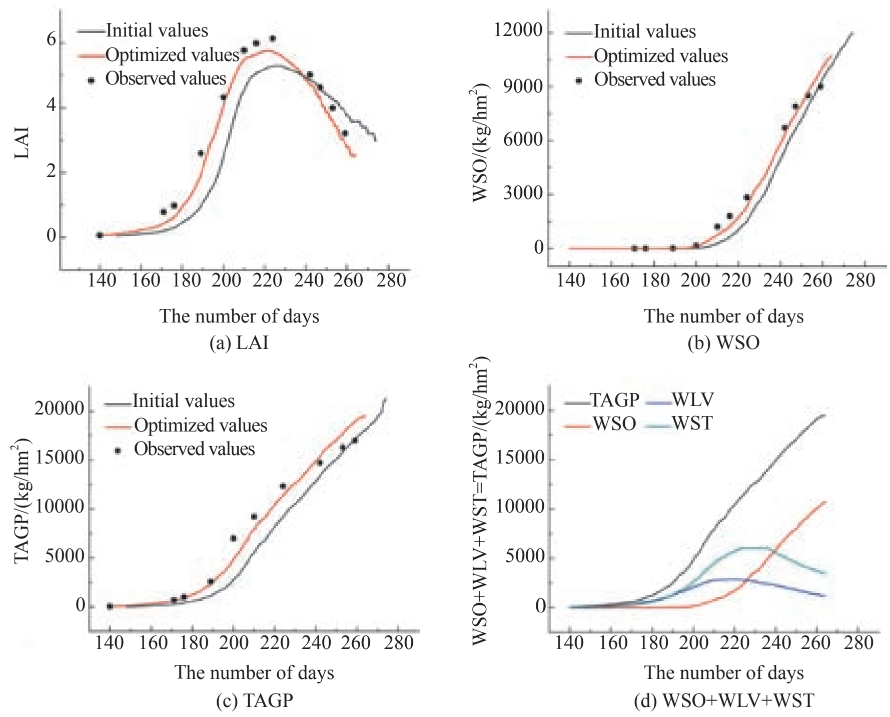


Fig. 7 Continuous simulation of rice growth parameters on time scale

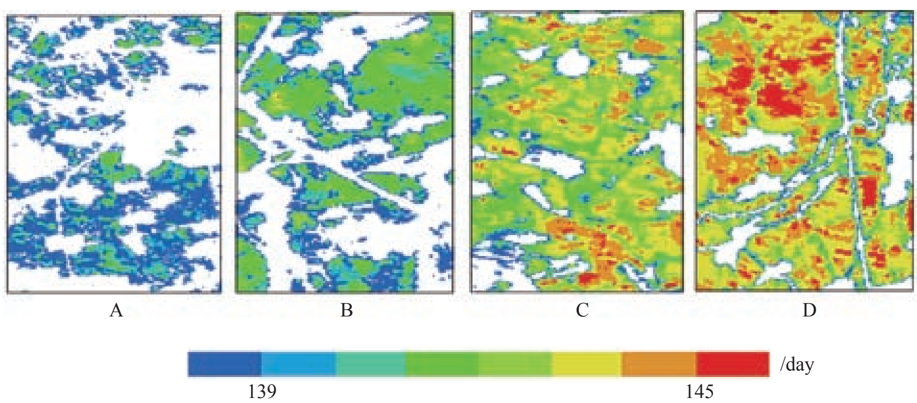


Fig. 8 The optimized results of IDTR of rice in study areas

Table 4 Average of four-day temperature observed values in study areas

/℃

The number of days	Study areas			
	A	B	C	D
136—139	14.8	13.1	10.4	9.7
138—141	16.7	14.5	12.7	11.3
141—144	18.4	16.8	14.2	12.8
142—145	19.2	18.1	15.8	14.6

With optimized IDTR, TSUMST and the climate and crop parameters of PAR and *T*, the last of which was estimated from remote sensing, WOFOST was driven to acquire the spatial distribution of rice growth parameters (Fig. 10). For comparison, simulated growth stages of study area A were regarded as the standard of the rice growth stages in the study. As shown in Fig. 10(a), the rice LAI of the four study areas were relative low after the transplant for about one month (Day 140). At the heading stage (Day 216), the rice LAI of four study areas were relative high and the relationship of the values of LAI of the four study areas was $LAI_A>LAI_B>LAI_C>LAI_D$. Because of rice growth entering reproductive stage at the mature stage (Day 259) and leaf aging, the values of rice LAI in the four study areas decreased. At the same time, comparing with the rice growth date of study area A, the rice growth date of the other study areas were delayed, so characteristic of the rice LAI of study area at the mature stage was $LAI_D > LAI_C > LAI_B > LAI_A$.

Because rice growth was still in vegetative period in Day 140, the values of WSO in study area were zero and did not increased before rice growth entered reproductive period from Fig. 10(b). The spatial distribution possessed the relationship of $WSO_A>WSO_B>WSO_C>WSO_D$. And the spatial distribution of rice WSO at mature stage had the some relationship at heading stage.

TAGP at the rice growth early stage were also small. At heading and mature stage, the spatial distribution of TAGP also possessed the relationship of $TAGP_A > TAGP_B > TAGP_C > TAGP_D$ (Fig. 10(c)).

The average simulated yield in the four study areas was 8724 kg/hm^2 and the average actual yield in Changchun was 6848 kg/hm^2, the relative error of simulated results in the region was 27.4%. It proved that continuous simulation of rice growth parameters on spatial scale with the region scale RS-WOPROSAIL is reliable.

5 CONCLUSIONS

A regional scale remote sensing-crop simulation assimilation framework model RS-WOPROSAIL performed spatial-time scale continuous simulation of rice growth parameters. The change characteristics of rice growth parameters on spatial-time scale was analyzed. The main outcomes in this study are shown as below.

(1) It is an effective approach to solve scaling- up problem that regionalization of the input parameters in the coupled model, which have the variability on regional scale, was established via remote sensing data retrieval.

(2) RS-WOPROSAIL model performed spatial-time scale continuous simulation of rice growth parameters, it made mechanism and universality higher. And established the foundation for analyzing the change characteristics of rice growth parameters on spatial-time scale.

(3) The simulation precision of growth parameters, including LAI and WSO as well as TAGP that were reported from the RS-WOPROSAIL model, is better than that of crop growth model, preferably reflecting the change characteristics of rice growth status on the spatial-time scale. The relative error between simulation yield and actual one was 27.4%, which indicated the model is reliable for the application on region scale.

(4) Because of the limitation of observed data, many parameters of coupled model WOPROSAIL were set as default or fixed values. At the same time, many basic problems about remote sensing have not been solved yet. The error should be made in retrieval of regional parameters with remote sensing information. In addition, the crop growth model under potential production level was established in this study, but the assimilated remote

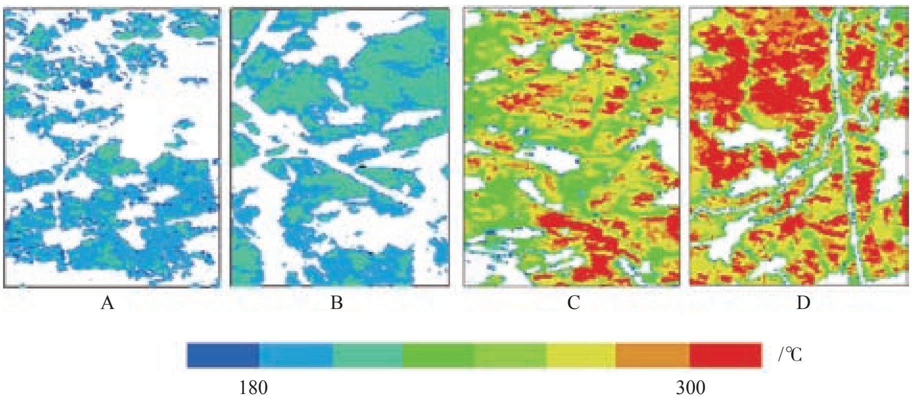


Fig. 9 The optimized results of TSUMST of rice in study areas

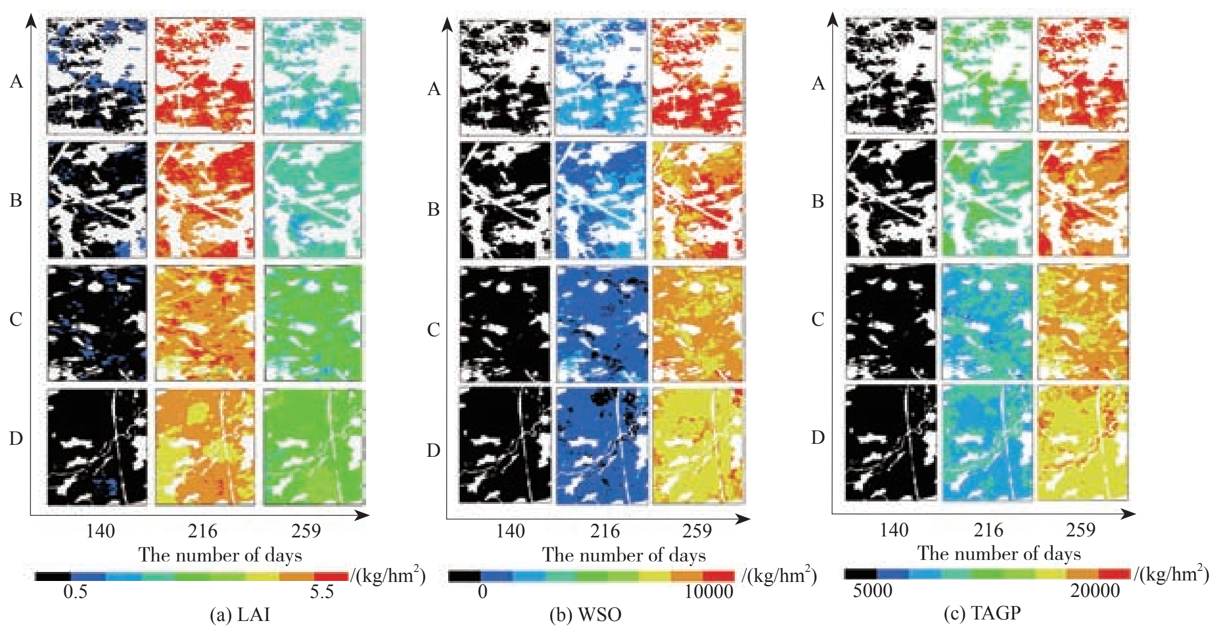


Fig. 10 Continuous simulation of rice growth parameters on spatial scale

sensing image contains information about water, nutrition, pest and disease damage and so on, which makes error exist in the assimilation process. All these factors resulted in the deviation between simulated results and actual ones, which needs more research and improvement.

In a word, The RS-WOPROSAIL model constructed with remote sensing data, crop growth model, and canopy radiative transfer model as well as particle swarm optimization algorithm effectively achieves the objective of rice growth parameters spatial-time scale continuous simulation. On that basis, the change characteristics of rice growth parameters on spatial-time scale were analyzed, providing the useful information for agriculture production and management.

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多源遥感与作物模型同化模拟作物生长参数时空域连续变化

吴伶，刘湘南，周博天，李露锋，谭正

中国地质大学(北京)信息工程学院，北京 100083

摘　要：本文将遥感信息与作物模型同化实现作物生长参数的时空域连续模拟，进而监测生长参数的时空域变化。首先将作物模型WOFOST(World food studies) 与冠层辐射传输模型PROSAIL耦合构建WOPROSAIL模型，利用微粒群算法(PSO)通过最小化从CCD数据获取的土壤调节植被指数观测值SAVI(soil adjusted vegetation index)与耦合模型得到的模拟值SAVI'之间差值优化作物模型初始参数。通过MODIS数据反演实现参数的区域化，并将区域参数作为优化后作物模型输入参数驱动模型逐像元计算生长参数，实现生长参数的时空域连续模拟与监测，最终建立区域尺度遥感-作物模拟同化框架模型RS-WOPROSAIL。结果表明：同化模型解决了作物模型模拟空间域和遥感信息时间域的不连续问题。模型模拟的叶面积指数(LAI)、穗重(WSO)、地上总生物量(TAGP)等生长参数较好地体现了水稻生长状况时空域变化，研究区水稻模拟产量与实际产量的误差为27.4%。

关键词：作物模型，PROSAIL模型，PSO算法，同化，作物生长参数，时空域连续模拟

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1 引　言

作物生长模型在田间尺度上对表征作物生长状况的叶面积指数LAI(Leaf Area Index)、地上总生物量TAGP(Total Above Ground Production)和穗重WSO(Weight of Storage Organs)等生长参数具有较好的模拟精度(邬定荣 等，2003；谢文霞 等，2006)，但当其在区域尺度上应用时，由于某些初始输入参数的空间异质性特点导致了其获取困难，限制了作物生长模型在区域尺度的应用(刘布春 等，2003)。因此，近年来，将遥感信息同化到作物生长模型模拟过程中成为作物生长模型区域化应用的一种有效途径。通过遥感数据的辅助既可改善作物生长模型的模拟精度(王纯枝 等，2005)，同时还可以准确、实时地获取区域尺度的模型输入参数(王人潮和黄敬峰，2002)。所以，将具有空间连续性的遥感信息与具有时间连续性的作物生长模型同化，有望实现作物生长模型在区域尺度的应用(Wit和Diepen，2007)，从而达到对作物生长状况进行时空连续模拟的目的。

目前，国内外围绕作物生长模型与遥感技术的同化研究主要有：利用遥感反演的冠层状态变量(如LAI、叶片氮积累量LNA等)校准作物模型的模拟过程或重新初始化、参数化作物模型来优化模型模拟过程(Clevers，1997；闫岩 等，2006；Dente 等，2008；朱元励 等，2010；谭正 等，2011)；通过冠层作物状态变量(如LAI)将冠层辐射传输模型与作物模型耦合，直接以遥感辐射观测本身去校准作物模型的模拟过程或重新初始化、参数化作物模型，达到优化模型的目的(Supit，1997；Guerif 和Duke，1998；

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第一作者简介：吴伶(1983—　)，男，博士研究生，主要从事遥感信息与过程模型耦合研究。E-mail: wl_19830807@sohu.com。

通信作者简介：刘湘南(1964—　)，男，教授，博士生导师，主要从事遥感信息分析与地学应用研究。E-mail: liuxncugb@163.com。

Weiss 等，2001；马玉平 等，2005)。前一种方法对遥感反演作物参数的准确性有较高要求，而后一种法通过直接比较反射率(或植被指数)对作物模型进行初始化和参数化，无作物参数反演环节带来的误差，故后一种方法成为学者们重点研究方向。

本文在作物生长模型WOFOST与冠层辐射传输模型PROSPECT+SAIL(PROSAIL)耦合的基础上，利用粒子群优化算法(PSO，Particle Swarm Optimization)同化从CCD影像获取的土壤调节植被指数SAVI(Soil Adjusted Vegetation Index)(Huete，1988)，重新初始化作物模型的关键参数，提高作物模型的模拟精度；利用遥感技术获取区域尺度天气等参数，驱动作物模型计算区域生长参数，建立区域尺度遥感-作物模拟同化框架模型(RS-WOPROSAIL)，实现对水稻生长参数时空域连续模拟，为时空数据建模与分析提供参考和新的思路。

2 研究区与数据

2.1 研究区概况

研究区位于吉林省长春市，其地理位置为125º03'—125º34'E，43º26'—44º05'N，地处东北平原。研究区属亚欧大陆寒温带大陆性气候，光照比较充足，热量适中。年平均气温4.9℃；年平均降水量594 mm，多集中在7、8月，最多可达311 mm；土壤以黑土为主，土质肥沃。研究区属于东北早熟单季稻稻作区，水稻品种以早粳稻中的吉粳系列为主。本文选取4个水稻种植区(A、B、C、D)作为研究区以及1个实测样本区E(125º09'E，43º51'N)。研究区及样本区位置如图1所示。

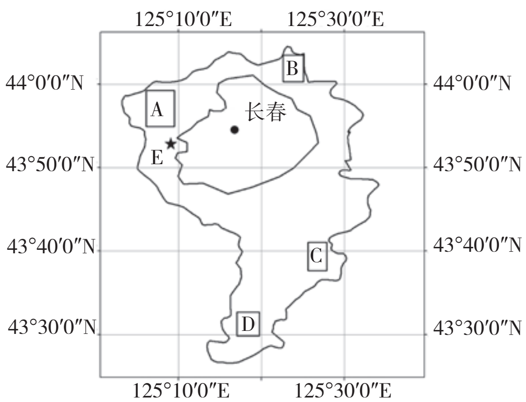


图1 研究区和样本区位置

2.2 数据获取

所需数据包括遥感数据、WOFOST和PROSAIL模型所需数据以及水稻实测数据。本文主要采用的遥感数据为环境与减灾小卫星CCD数据，其具有高空间分辨率(30 m)、高时间分辨率(4 d)以及大成像幅宽(360 km或720 km)等特点。本文获取了从2009年5月至9月的12景数据质量较好的CCD数据，数据获取时间分别为5月20日、6月20日、6月25日、7月8日、7月19日、7月29日、8月4日、8月12日、8月30日、9月4日、9月10日和9月16日，涵盖了水稻整个生长期。利用中国资源卫星应用中心提供的每个波段的定标系数对CCD数据进行辐射定标处理，利用研究区一幅已校正TM影像作为基准影像对其进行几何校正，采用6S模型对影像进行大气校正处理。另外，选择MODIS数据中的MOD09(地表反射率)、MODIS-NDVI以及陆地表面温度LST (Land Surface Temperature)等3种产品进行参数区域化扩展。

本文是对潜在生产力水平下的水稻生长模拟，所以WOFOST模型所需参数主要为天气和作物参数，天气参数包括气温T、太阳辐射等。样本区E位置与长春气象站位置(125º13'E，43º54'N)接近，故样本区气温数据选用国家气象信息中心的中国地面气候资料日值数据集长春站2009年间长春地区的逐日数据。样本区太阳辐射R_S由式(1)计算得到(Doorenbos和Pruitt，1977)。

$$R_s = \left(a_s + b_s \frac{n}{N}\right) R_a \tag{1}$$

式中，a_s和b_s为经验常数，分别取0.25和0.5。n为日照时数，可由长春气象站获取。N为可日照时数。R_a为大气上界入射辐射。

在样本区E样地内测量PROSAIL模型所需的土壤反射率、主要生长期水稻叶片叶绿素含量、干物重、水分含量以及表征水稻生长状况的LAI、TAGP、WSO等生长参数，每个时期测量40组样本数据，取其平均值作为每个时期样本区的实测值。

3 遥感–作物模型同化技术

首先通过叶面积指数LAI将潜在生产力水平下作物生长模型WOFOST与冠层辐射传输模型PROSAIL耦合构建WOPROSAIL模型，利用微粒群算法(PSO)通过最小化CCD影像观测值SAVI与潜在生产力水平下耦合模型模拟值SAVI’之间的差值优化作物模型的初始化参数移栽日期IDTR(Day of Transplanting)和

播种-移栽期内有效积温TSUMST (Temperature Sum from Sowing to Transplanting)，以提高作物模型的模拟精度，建立田间尺度的遥感-作物模拟同化框架模型RS-WOPROSAIL；利用MODIS数据反演得到的区域化气温T、光合有效辐射(PAR，photosynthetically Active Radiation)等参数驱动模型逐像元计算生长参数(LAI、WSO、TAGP)，在田间尺度基础上建立区域尺度遥感-作物模拟同化框架模型RS-WOPROSAIL，从而实现生长参数的时空域连续模拟。

3.1 作物生长模型WOFOST与冠层辐射传输模型PROSAIL耦合

本文采用WOFOST作物生长模型，研究潜在生产力水平下水稻的生长状况WOFOST模型主要模拟包括作物发育、CO_2同化、呼吸消耗、干物质分配、LAI增长、土壤水分平衡、作物蒸腾等过程(Boogaard 等，1998)。该模型有3种模拟水平：潜在生产力水平(适宜水分和营养条件)、水分限制作物生长水平(雨养条件)和营养限制作物生长水平(氮、磷和钾供应不足)，潜在生长力水平下，WOFOST通过计算作物生长的有效积温确定作物发育阶段，当作物日有效积温累积到完成某个发育期所需的有效积温总和，则代表作物已生长到该发育阶段。WOFOST通过考虑大气透射系数、直射光和漫射光、冠层对光的反射、散射以及吸收等来描述冠层对光的截获，通过截获的光合有效辐射PAR来计算作物潜在总光合产物。作物生产的总光合产物中部分被用于维持呼吸和生长呼吸，剩余部分转化成结构干物质并在根、茎、叶和贮存器官中进行分配，分配系数随发育阶段的不同而不同，各器官总量通过对日同化量进行积分得到。叶片按叶龄分组，在作物发育过程中，叶片随叶龄增大而老化死亡，从而影响光截获(图2)。

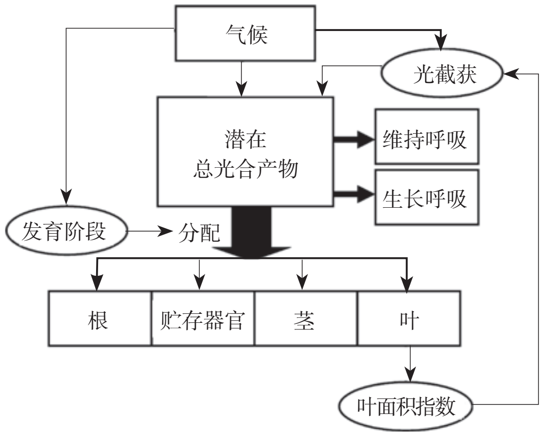


图2 潜在生长力水平下WOFOST模型简化结构

PROSAIL模型是PROSPECT+SAIL模型的综合。PROSPECT模型是一个基于“平板模型”的辐射传输模型(Jacquemoud 和Baret，1990)，它通过模拟叶片从400 nm到2500 nm的上行和下行辐射通量而得到叶片的反射率和透射率。SAIL模型是一个冠层二向反射率模型(Verhoef，1985)，LAI是其输入参数之一。当给定冠层结构参数和环境参数时，可以计算任何太阳高度和观测方向的冠层反射率。PROSAIL模型是将通过PROSPECT模型获取的植被叶片反射率和透射率输入SAIL模型，最终得到植被冠层反射率。

当给定作物理化参数和区域天气参数，通过LAI将WOFOST模型与PROSAIL模型耦合构建的WOPROSAIL模型可将WOFOST模型模拟得到的作物LAI输入PROSAIL模型，从而得到植被冠层反射率(图3)。

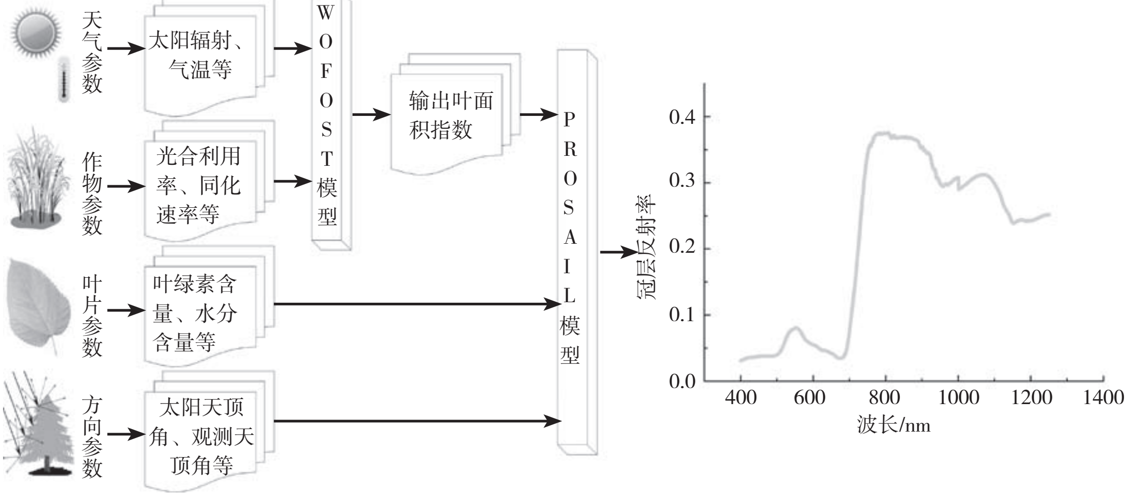


图3 潜在生产力水平下WOPROSAIL耦合框架

根据植被理化、几何和天气参数获得植被冠层反射率，为利用遥感辐射观测调整优化作物模型的模拟过程或重新初始化、参数化作物模型奠定了基础。

3.2 优化参数选择

长春地区是中国受低温冷害严重的地区之一，为保证水稻的正常生长发育，该地区一般采用大棚育苗方式来提高有效积温，而播种—移栽期内(大棚育苗期间)的气温是无法通过空间插值或遥感反演获得的，且该阶段的有效积温TSUMST对于准确模拟水稻生长过程非常重要。移栽日期IDTR在区域范围内具有空间异质性特点，在区域尺度上也不易准确获取。

通过对2个参数进行敏感性分析，研究其对作物模拟结果的影响程度，即在其他参数值不变的情况下，测试TSUMST值降低10%(或IDTR提前和推迟10天)，模型模拟结果(最大LAI、最终WSO和TAGP)变化百分率(表1)。可以看出，IDTR推迟10 d或TSUMST降低10%，最大LAI分别降低11.39%和10.57%，这对光合作用将产生影响。最终WSO和地上总生物量TAGP的变化范围也分别是4.5%—9.78%和6.1%—9.09%，这说明IDTR和TSUMST对作物发育和生物量的形成有较大影响。

表1 IDTR和TSUMST敏感性分析 /%

	IDTR		TSUMST
	提前10 d	推迟10 d	降低10%
最大LAI	7.85	− 11.39	− 10.57
最终WSO	4.58	− 9.78	− 8.42
TAGP	6.1	− 9.09	− 8.18

综上所述，本文将区域尺度上不易准确获取并对作物模型模拟结果有较大影响的IDTR和TSUMST等2个参数作为模型待优化参数。

3.3 参数区域化

由于地表状况的空间非均一性，将点模型推广到区域应用，需将耦合模型中的参数进行区域化处理。

本文选择潜在生产力水平下的WOFOST模型模拟水稻生长，故其主要受光合有效辐射PAR和气温T等天气参数影响。对于PAR，基于时间分辨率与WOFOST模型模拟步长相同的MODIS数据根据辐射传输方程对PAR进行反演从而获取其空间分布数据(刘荣高 等，2004)；T参数的空间插值结果很大程度受气象站点密度和分布特征等影响，由于研究区内只有一个气象站点，无法利用空间插值方法获取T的空间分布情况，故在T与浓密植被冠层LST近似的理论基础上，利用MODIS数据中的NDVI和LST产品，采用NDVI-T_s空间法获取T的空间分布数据(齐述华 等，2005)。

研究区内水稻主要为早粳稻中的吉粳系列品种，其生育期等遗传特性大体一致，故对于WOFOST模型中的大部分作物参数(如比叶面积、净光合速率、干物质分配系数等)，利用实测数据以及相关文献(武志海 等，2009)对其作统一取值处理。对于与温度有关的作物参数如移栽到开花有效积温(TSUM1)、开花到成熟有效积温(TSUM2)等，则根据上述遥感方法获取的T数据计算获得其空间分布。同时对WOFOST模型进行适应性调整，以使其适应长春地区的水稻生长模拟。

PROSAIL模型叶片参数中的叶片叶绿素和水分含量分别基于绿度归一化植被指数(GNDVI)(Gitelson，等，1996)和归一化水分指数(NDWI)(Gao，1996)利用MODIS数据反演其空间分布数据。研究区内土壤类型主要是黑土，故冠层参数中的土壤反射率使用实测数据，方向参数(太阳天顶角、观测天顶角、双向相对方位角等)空间分布情况可从CCD影像文件中获取。其他参数如干物质含量、类胡萝卜素、棕色色素、叶片结构系数、平均叶倾角、散射辐射比例和热点参数等根据样本区实测数据或经验值设定固定值。

3.4 优化算法

最优化是在遥感数据与作物模型同化过程中，实现模拟值与遥感观测值差异最小的重要工作。优化算法的自身性能及其对先验知识的依赖性在很大程度上影响了同化后作物模型的实际应用能力(李存军 等，2008)。本研究使用的优化算法为原理简单、易于耦合集成的微粒群算法(PSO)(Kennedy 和Eberhart，1995)。此算法的基本思路是：群体中的每一个体被视为多维空间中以一定速度飞行的，没有质量和体积的微粒，每一个微粒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，并依据每个微粒对环境的适应度将个体逐步移到较优的

位置，并最终搜索到最优位置，即问题的最优解。最优位置是由以微粒位置坐标值作为输入变量的代价函数决定的。

本文中空间维数代表待优化参数的个数(2个)。微粒个数为待优化的2个参数在取值范围内各自随机取值组合的组数(25组)，每迭代一次随机值改变一次，如此连续直至最小化代价函数值。本研究设定的最大迭代次数为400，若连续有100次迭代的代价函数值没有发生改变，则停止迭代。

3.5 区域尺度遥感–作物模拟同化框架构建

本文利用耦合模型WOPROSAIL模拟得到的植被冠层反射率计算光谱指数SAVI’，通过同化由CCD影像获取的光谱指数SAVI(式(2))，最小化SAVI和SAVI’之间的差值。在此过程中引入PSO优化算法，不断调整WOFOST中待优化参数值(IDTR和TSUMST)，从而调整WOPROSAIL模拟得到的SAVI’，使得其与SAVI值不断收敛，直至相差最小，然后将调整后的待优化参数值作为作物生长模型的初始值，运行WOFOST，模拟得到较为准确的水稻生长动态过程，从而建立田间尺度遥感-作物模拟同化框架模型RS-WOPROSAIL(图4)。SAVI计算公式和代价函数表达式分别为：

$$\mathrm{SAVI}=\frac{\rho_{\mathrm{nir}}-\rho_{\mathrm{red}}}{\rho_{\mathrm{nir}}+\rho_{\mathrm{red}}+0.5}(1+0.5) \tag{2}$$

$$Q=\frac{1}{p}\sqrt{\sum_{i=1}^{i=p}(x_i-y_i)^2} \tag{3}$$

式中，ρ_{red}和ρ_{nir}分别代表CCD影像的红光(3波段)和近红外波段(4波段)，Q为代价函数值，P为外部同化数据个数，x_{i}为利用WOPROSAIL模型模拟的某一时间点植被冠层反射率计算得到的SAVI’，y_{i}为利用某一时间点的CCD影像计算得到的SAVI。

在上述建立的田间尺度RS-WOPROSAIL基础上，利用参数区域化获取的天气参数、叶片参数、作物参数以及方向参数等数据逐像元驱动田间尺度RS-WOPROSAIL，获得IDTR和TSUMST等2个优化参数的空间分布数据，进一步利用这2个优化参数、天气参数以及作物参数逐像元驱动WOFOST模型，建立区域尺度遥感-作物模拟同化框架模型(图5)。

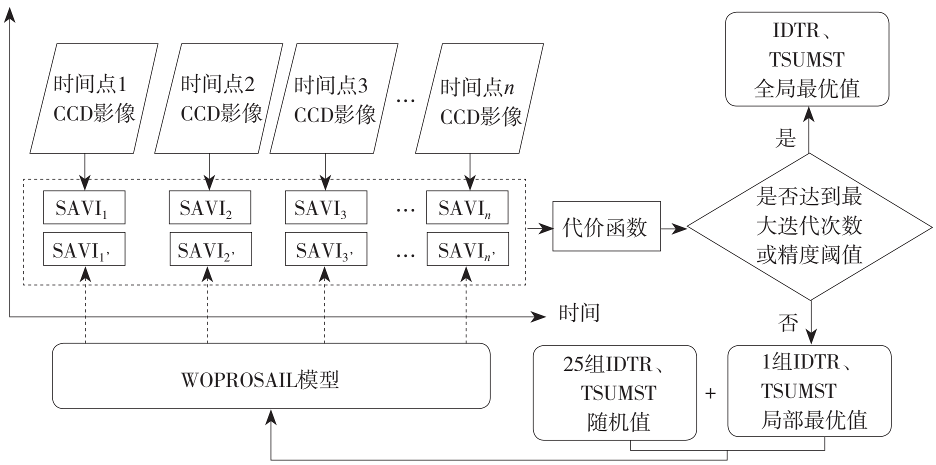


图4 基于PSO算法的田间尺度RS-WOPROSAIL同化框架模型结构

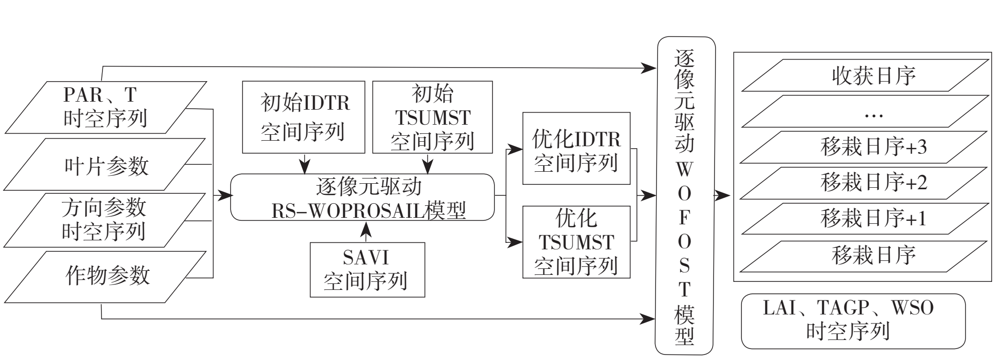


图5 区域尺度RS-WOPROSAIL同化框架模型结构

4 作物生长参数时空域连续模拟

4.1 生长参数时空域连续模拟

利用构建的区域尺度RS-WOPROSAIL同化框架模型，可实现水稻生长参数时空域上的连续模拟，解决了作物模型模拟空间域上和遥感信息时间域上的不连续问题。通过引入遥感信息，同化模型实现了从点模型到面模型的升尺度过程。遥感信息反演水稻生长参数受云雨以及时间分辨率等影响，当水稻生长期内某一时间点受云雨影响而导致遥感信息不准确或因时间分辨率过低而处于遥感信息“空白期”时，遥感反演的精度会受到影响，而同化模型降低了云雨影响，其时间分辨率也达到1天，避免了模型模拟出现“空白期”问题。RS-WOPROSAIL同化框架模型是基于机理性强的作物生长模型和冠层辐射传输模型，相比遥感信息统计反演，其普适性也更高。因此，利用本文构建的区域尺度RS-WOPROSAIL同化框架模型可获得生长期内任一时间点(以1天为步长)水稻生长参数的空间分布数据(图6)，从而了解某个时期区域内水稻生长状况，为农业生产以及管理提供有效信息。

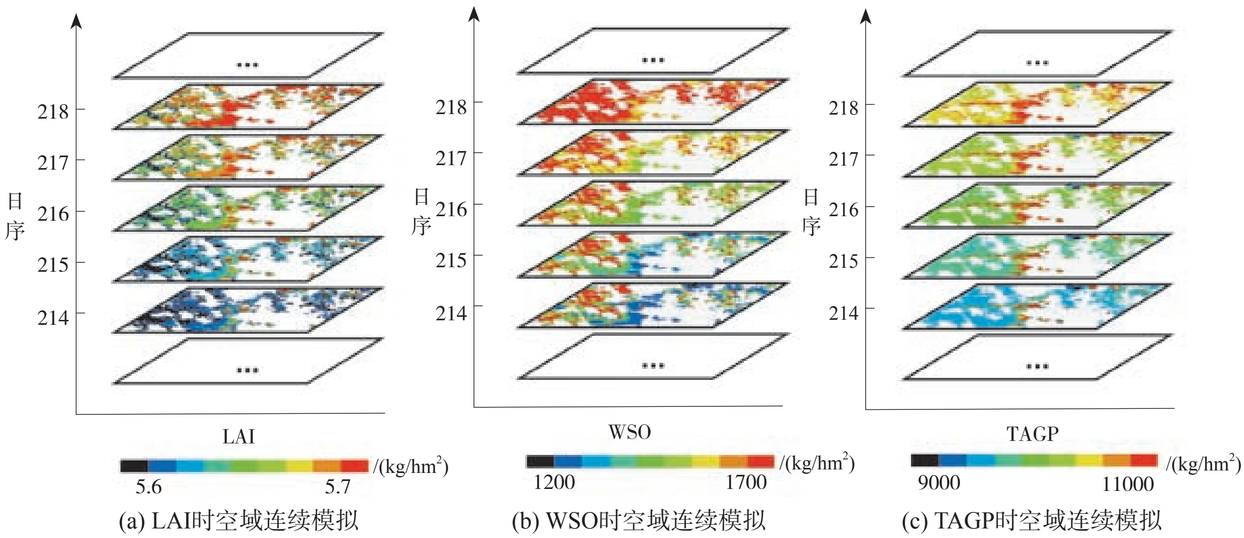
4.2 作物生长参数时间域变化特征分析

运行同化模型之前，首先给定一组与实测值不同的模型待优化初始参数值，如IDTR定为147 d(5月27日)、TSUMST定为150℃。运行RS-WOPROSAIL同化框架模型，同化从CCD数据中获取的植被指数SAVI，得到优化的IDTR、TSUMST(表2)。经过优化后的IDTR与样本区实际IDTR相差仅2 d，同化模型模拟的开花日期IDAN (day of anthesis)误差为3 d，模拟的成熟日期IDMA (day of mature)误差为4 d。TSUMST与实测值之间的差距也大大减少。

表2 水稻移栽日期IDTR和播种-移栽期内有效积温TSUMST优化结果

	TSUMST/℃	IDTR/d	IDAN/d	IDMA/d
初始值	150	147	222	274
优化值	194	139	219	264
实测值	225	137	216	260
初始值与实测值误差	75	10	6	14
优化值与实测值误差	31	2	3	4

将优化的IDTR和TSUMST输入WOFOST模型，模拟水稻的生长过程。比较RS-WOPROSAIL模型优化模拟值、WOFOST模型初始模拟值和实测值可以看出(图7)，优化后水稻LAI、WSO、TAGP的模拟结果得到改进，较好地体现了水稻LAI、WSO、TAGP随生长期变化的过程。水稻LAI优化模拟值在移栽后(第139天)逐渐增大，直至抽穗开花期(第222天)达到最大值(5.76)，之后水稻生长进入生殖生长期，同时由于叶片老化，LAI优化模拟值逐渐减少(图7(a))。进入生殖生长期后，水稻生长主要以穗的增长为主，故WSO优化模拟值的增长速率加快(图7(b))。水稻生长后期茎、叶陆续老化死亡，茎重WST(weight of stems)和叶重WLV(weight of leaves)逐渐减少，但同时WSO持续增加，故水稻TAGP优化模拟值在生长期内



(a) LAI时空域连续模拟 (b) WSO时空域连续模拟 (c) TAGP时空域连续模拟

图6 A研究区水稻LAI、WSO及TAGP时空域连续模拟

仍持续增加(图7(c) (d))。经遥感数据同化后，水稻产量(最终WSO)模拟值相对误差由优化前的33.6%降至优化后的18.8%，水稻最终TAGP模拟值相对误差也由29.3%降至14.5%(表3)，改善了水稻生长的模拟效果，说明RS-WOPROSAIL模型是可靠的，为区域尺度RS-WOPROSAIL模型构建奠定了基础。

4.3 作物生长参数空间域变化特征分析

在进行作物生长参数空间域连续模拟之前，首先运行RS-WOPROSAIL同化框架模型获取优化的水稻IDTR和TSUMST区域分布。优化的研究区水稻IDTR空间分布情况为$IDTR_D>IDTR_C>IDTR_B>IDTR_A$(图8)，这是由于研究区内的气温呈西北-东南方向逐级降低(表4)，而只有日平均气温稳定在13℃以上时，才达到水稻移栽适宜温度指标，故研究区西部和北部的IDTR一般比东部和南部的IDTR早。

为保证水稻的正常生长，IDTR晚的区域需要通过大棚育苗的方式获取更多TSUMST，以弥补外部气

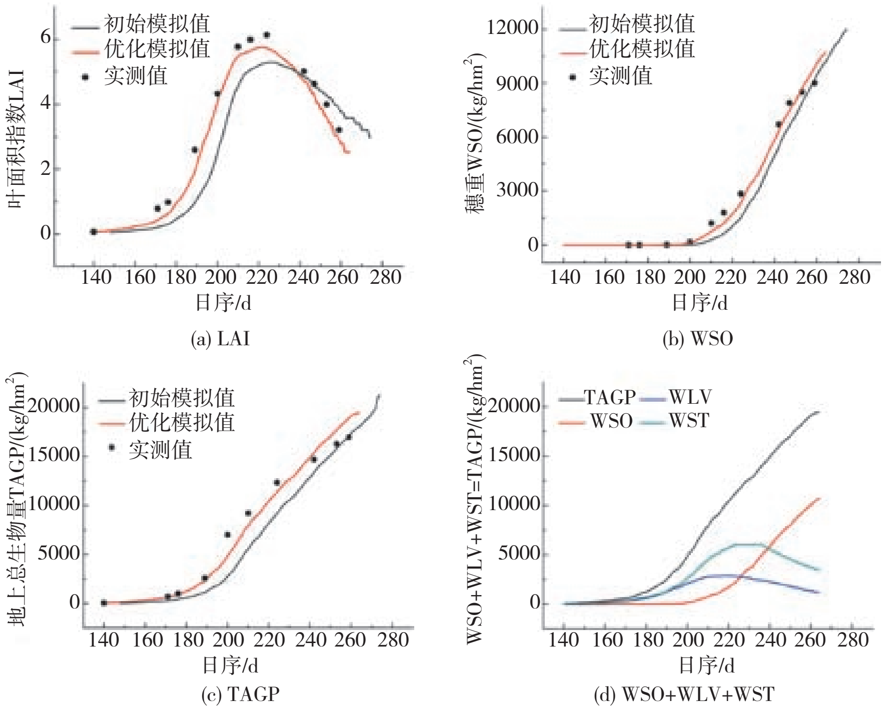


图7 水稻生长参数时间域连续模拟

表3 水稻产量及最终TAGP优化模拟结果

	初始模拟值/(kg/hm^2)	优化模拟值/(kg/hm^2)	实测值/(kg/hm^2)	初始值与实测值误差/%	优化值与实测值误差/%
产量	12007	10678	8987	33.6	18.8
最终TAGP	21981	19465	16994	29.3	14.5

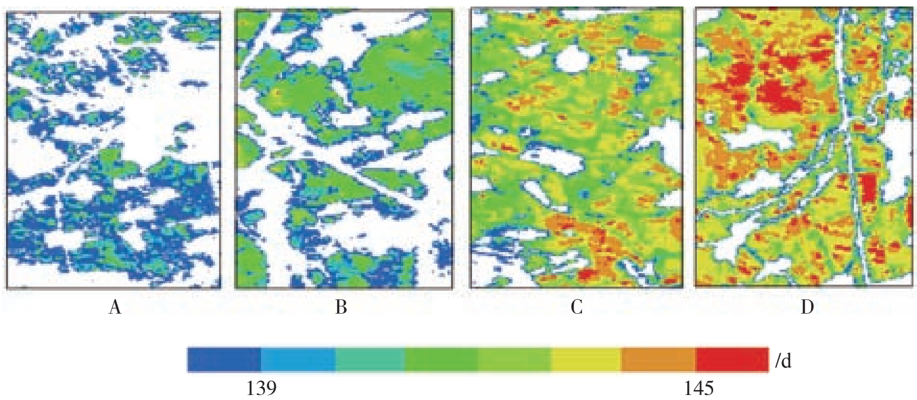


图8 研究区水稻IDTR优化结果

温过低而阻碍水稻生长的问题，故优化的研究区水稻TSUMST空间分布为$TSUMST_D$>$TSUMST_C$>$TSUMST_B$>$TSUMST_A$(图9)。

表4 研究区连续4日平均气温观测值 /℃

日序/d	研究区			
	A	B	C	D
136—139	14.8	13.1	10.4	9.7
138—141	16.7	14.5	12.7	11.3
141—144	18.4	16.8	14.2	12.8
142—145	19.2	18.1	15.8	14.6

将遥感信息反演获得的天气、作物等参数与优化的IDTR和TSUMST输入WOFOST模型，即得到水稻生长参数的空间分布信息(图10)。为便于比较，此后文中涉及的水稻生长期都以A研究区的模拟生长日期为标准。由图10(a)可知，移栽后大约一个月(第140天)，4个研究区水稻LAI都较低。在抽穗开花期(第216天)，4个研究区水稻LAI基本上都较高，并呈现LAI_A>LAI_B>LAI_C>LAI_D的空间变化特征。由于水稻在成熟期(第259天)主要进行生殖生长以及叶片老化等原因，研究区内水稻LAI值降低，同时相对A研究区，其他研究区的水稻生长日期相对延后，故其空间变化呈现LAI_D> LAI_C >LAI_B> LAI_A的特征。

图10(b)是水稻WSO各个时期的空间分布情况。由于第140天水稻还处在营养生长期内，4个研究区的WSO都为0，直至抽穗开花期才正式进入生殖生长期，此时WSO开始增长，其空间分布呈现WSO_A > WSO_B > WSO_C > WSO_D的空间变化特征。成熟期水稻WSO的空间分布也呈现相同的空间分布特征。

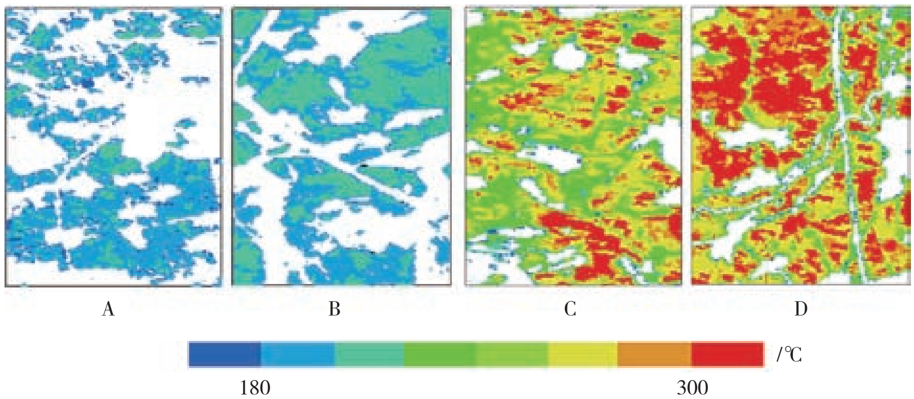


图9 研究区水稻TSUMST优化结果

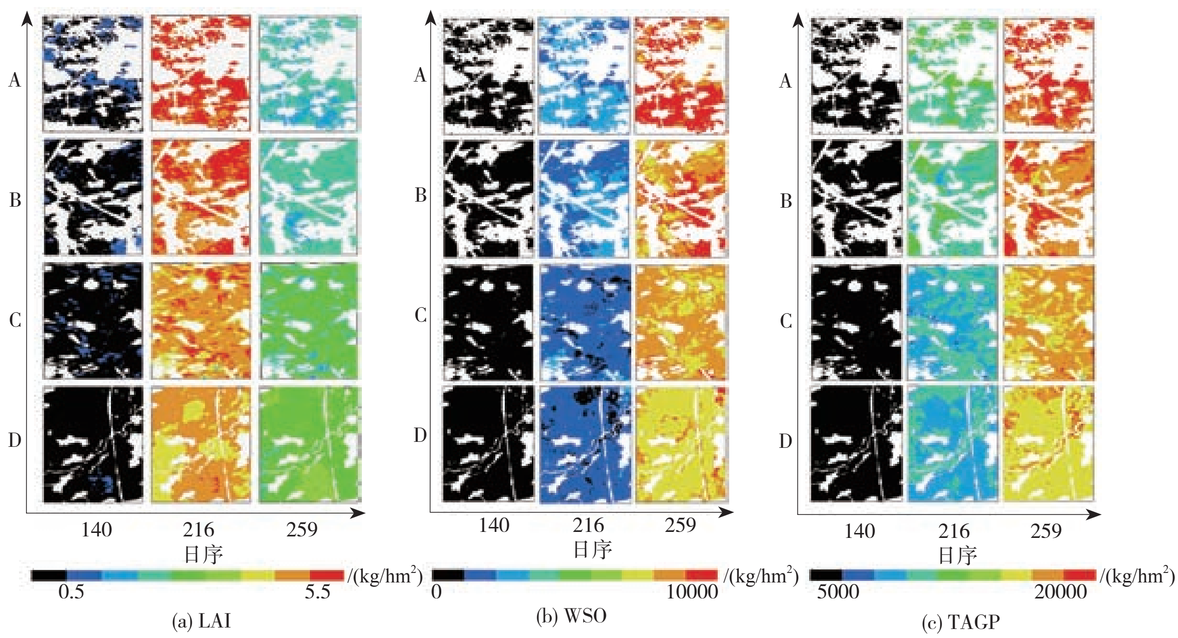


图10 水稻生长参数空间域连续模拟

水稻TAGP在生长初期也较小(图10(c))。在抽穗开花期与成熟期，TAGP的空间分布也呈现$TAGP_A$>$TAGP_B$>$TAGP_C$>$TAGP_D$的特征。

经统计，4个研究区的水稻模拟产量(最终WSO)平均值为8724 kg/hm^2，长春市市辖区水稻实际产量为6848 kg/hm^2，区域模拟结果误差为27.4%，这说明遥感信息的调整使作物模型模拟结果与实测结果较吻合，从而证明区域尺度RS-WOPROSAIL模型的水稻生长参数空间域连续模拟是可靠的。

5 结 论

本文通过构建的区域尺度遥感-作物模拟同化框架模型RS-WOPROSAIL实现了水稻生长参数的时空域连续模拟，在此基础上分析了水稻生长参数的时空域变化特征。主要结论有：

(1) 利用遥感数据反演耦合模型中具有空间异质性特点的输入参数，为解决模型尺度问题提供了一种有效途径。

(2) 构建的区域尺度RS-WOPROSAIL同化框架模型实现了水稻生长参数在时空域上的连续模拟，其机理性、普适性更高，为进行水稻生长参数时空域变化特征分析奠定了基础。

(3) 通过同化模型模拟得到的水稻叶面积指数LAI、穗重WSO、地上总生物量TAGP等生长参数较之作物模型模拟结果得到改进，较好地体现了其在时空域上的变化特征。同化模型模拟的研究区水稻平均产量与实际平均产量误差为27.4%，说明模型在区域尺度上的应用是可靠的。

(4) 由于受地面实测资料的限制，WOPROSAIL耦合模型中的很多参数只能取默认值或固定值，未能探讨这些参数在区域上的变化。同时，卫星遥感方面也有许多基础性问题没有解决，从而导致遥感信息反演模型区域化参数存在一定误差。另外，本文建立的是潜在生产力水平下的作物模型，而同化的遥感信息包含水分、营养以及病虫害等因素，这使得同化过程存在误差。这些因素导致模拟结果与实际情况存在偏差，还需深入研究和改进。

综上所述，利用遥感数据、作物生长模型WOFOST、冠层辐射传输模型PROSAIL以及微粒群算法PSO等结合构建的区域尺度遥感-作物模拟同化框架模型RS-WOPROSAIL，有效地实现了水稻生长参数在时空域上的连续模拟，在此基础上分析水稻生长参数时空域变化特征，为农业生产及管理提供了有效信息。

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