Establishment of Winter Wheat Regional Simulation Model Based on Remote Sensing Data and Its Application*

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ABSTRACT

Accurate crop growth monitoring and yield forecasting are significant to the food security and the sustainable development of agriculture. Crop yield estimation by remote sensing and crop growth simulation models have highly potential application in crop growth monitoring and yield forecasting. However, both of them have limitations in mechanism and regional application, respectively. Therefore, approach and methodology study on the combination of remote sensing data and crop growth simulation models are concerned by many researchers. In this paper, adjusted and regionalized WOFOST (World Food Study) in North China and Scattering by Arbitrarily Inclined Leaves-a model of leaf optical PROperties SPECTra (SAIL-PROSFPECT) were coupled through LAI to simulate Soil Adjusted Vegetation Index (SAVI) of crop canopy, by which crop model was re-initialized by minimizing differences between simulated and synthesized SAVI from remote sensing data using an optimization software (FSEOPT). Thus, a regional remote-sensing-crop-simulation-framework-model (WSPFRS) was established under potential production level (optimal soil water condition). The results were as follows: after re-initializing regional emergence date by using remote sensing data, anthesis, and maturity dates simulated by WSPFRS model were more close to measured values than simulated results of WOFOST; by re-initializing regional biomass weight at turn-green stage, the spatial distribution of simulated storage organ weight was more consistent with measured yields and the area with high values was nearly consistent with actual high yield area. This research is a basis for developing regional crop model in water stress production level based on remote sensing data.

Key words: crop growth simulation, remote sensing data, coupling model, winter wheat, North China

1. Introduction

Accurate crop growth monitoring and yield forecasting are significant to the food security and the sustainable development of agriculture. Crop growth simulation models dynamically describe the growth, development and yield formation processes driven by climate and soil conditions. Therefore, these mechanistic models are useful tools for crop production monitoring and forecasting. However, the application at regional scale is limited by the lack of spatial information on input variables, initial conditions, and model parameters (Liu et al., 2002), such as sowing date, initial biomass, LAI (leaf area index), and available soil moisture as well. Remote sensing method, which can dynamically provide information on crop conditions during the growing season over large areas, has potential in crop growth monitoring and yield estimation on regional scale. However, it has limitation in mechanism, which just describes the instantaneous physical condition of cannopy. It can be seen that crop model and remote sensing data have their own advantages and limitaions. Therefore, combination of these two factors was concerned by researchers (Wiegand et al., 1979).

Several strategies of coupling remotely-sensed observations and crop models have been discussed (Maas, 1988a; Fischer et al., 1997; Moulin et al., 1998). The first avenue is called forcing strategy, in which driving variables or state variables (such as LAI) of models are updated by corresponding values derived from remote sensing data (Delecolle and Guerif, 1988; Karvonen et al., 1991; Yu and Driessen, 2003). However, it is difficult to obtain enough remote sensing data to meet

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the needs of crop models at daily time steps because of the satellite overpass repeat cycle and the occurrence of clouds. The second way, called recalibration strategy, uses several available remote sensing data during the crop growing season to re-calibrate the value of some parameters or initial conditions (Maas, 1988b; Clevers and van Leeuwen, 1996). The approach of directly using radiometric information to adjust crop models is also called assimilation strategy (Bouman, 1991; Guerif and Duke, 1998, 2000; Moulin et al., 2001; Stern et al., 2001; Doraiswamy et al., 2003), which couples a radiative transfer model to a crop model. It describes effects of enviroment conditions on crop growth and development in complete mechanism. The research of assimilating strategy includes the application of canopy radiative transfer model and optimizing methods, the selection of re-parameterizing/re-initializing variables and regionalization of crop model as well.

In the present study, based on the adaptation and regionalization of crop model for winter wheat in North China, a regional remote sensing crop simulation framework model was established under potential production level for winter wheat using assimilation strategy. The approach on using remote sensing data to re-calibrate crop model was investigated through some application simulations.

2. Materials

2.1 *Study area*

The study area, located in the Huabei Plain in North China (33°-41°N, 111°-123°E), is the largest alluvial plain of eastern Asia. It is situated on south of the Great Wall, west of the Taihang Mountains, and north of the Huaihe River. It mainly includes the Provinces of Hebei, Henan, and Shandong, the northern parts of the provinces of Anhui and Jiangsu, and the municipalities of Beijing and Tianjin, covering an area of about 528125 km^2, most of which are less than 50 m ASL (above sea level). Cultivated land areas account for more than 80% of the total area in this region.

2.2 *Data*

Daily maximum and minimum temperature, precipitation, solar radiation (or sunshine hours), wind speed, and vapor pressure were obtained from 80 weather stations in 1971-2003 to describe regional climate conditions. Some field observation data including phenological development stage, dry matter weight of leaf, stem and storage organ and LAI each 10 days for winter wheat in 4 yr were acquired from Gucheng, Tai'an, and Zhengzhou Agrometeorological Stations to adjust WOFOST model in local level. Winter wheat variety and phenological development data from 48 agrometeorological stations in 12 yr were collected to establish values of some model parameters at the regional scale. Eleven images of MODIS data in 2002-2003 were acquired for North China to re-initialize crop model. The first two bands of MODIS data were calibrated, and corrected for atmospheric attenuations. Digital counts were calibrated to radiances to obtain surface reflectance.

3. Establishment of regional remote sensing crop simulation framework model

The WOFOST model (Supit et al., 1994) based on adjustment and regionalization in North China and adjusted SAIL-PROSPECT model (Verhoef, 1984; Jacquemoud and Baret, 1990) were coupled through LAI to simulate Soil Adjusted Vegetation Index (SAVI) of crop canopy. Using the FSEOPT optimization software (Stol et al., 1992), initial conditions or crop parameters of the WOFOST model were re-initialized or reparameterized by minimizing differences between simulated and remote sensing monitoring SAVI values. Thus, a regional remote sensing crop simulation framework (WOFOST-SAIL-PROSPECT-FSEOPT-REMOTE-SENSING, WSPFRS) model was established under potential production level (optimal soil water condition) (Fig.1).

3.1 *Adaptation of WOFOST model in North China*

The World Food Study (WOFOST 7.1) model is used in the study. It is a mechanistic crop model, which allows dynamically simulating the phenological development and the growth processes on the basis of crop genetic properties and environmental conditions. The cultivar-specific values of thermal time, maximum

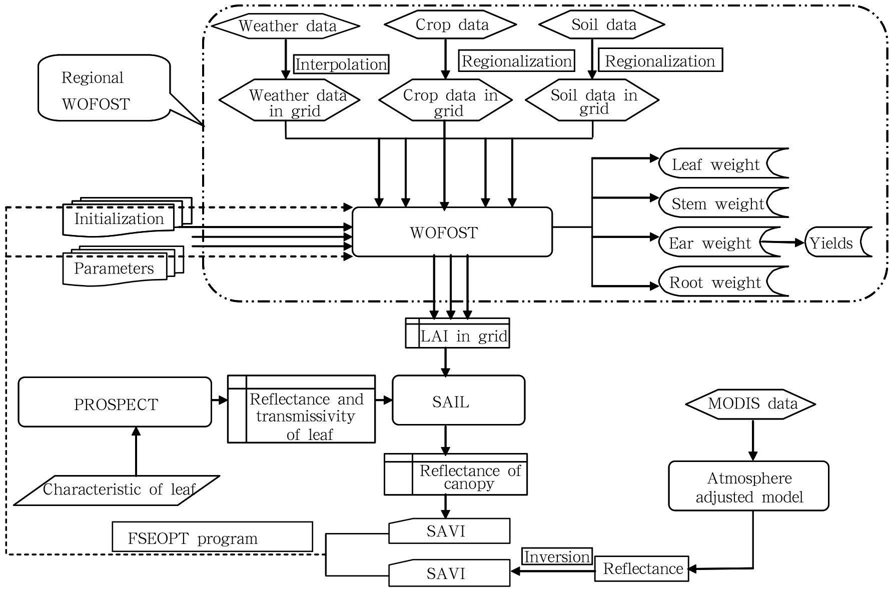

Fig.1. Structure chart of regional remote sensing crop simulation framework model (WPSFRS model) under potential production level.

assimilated rate of CO_2, assimilation conversion coefficients, specific leaf area, partitioning fractions, and some soil parameters acting on water transmission are important inputs. WOFOST can be used to simulate different crops or different varieties of the same crop through adjusting some parameters.

Due to long-term inheritance and variation, crops adapt to the specific-region climate conditions in the cultivated areas and form different climate-ecological types. Compared with Europe, there is lower temperature in winter and a longer period of over-winter dormancy as well as higher temperature in early summer during the growing season of winter wheat in North China. Thus, it is essential to adjust relative parameters and improve some procedures in WOFOST by using local field observed data, if this model will be applied in North China.

In the present study, some parameters of WOFOST under potential production level were adjusted for winter wheat in North China using field observed data from different years and different varieties of winter wheat grown under different climates. The results showed that the correlative coefficients of simulated and observed emergence, anthesis, and maturity are 0.68, 0.95, and 0.97, respectively, and the relative mean error of simulated maturity was less than 5.0%. The relative mean error of potential weight of above-ground dry matter estimates at maturity was 7.0%. These results showed that adjusted WOFOST model has good simulation ability at the local scale in North China.

3.2 *Regionalization of WOFOST in North China*

For the purpose of applications at regional scale, crop growth simulations need scaling-up. In this study, weather data from 80 weather stations were interpolated into the 25 km×25 km grids using IDW (Inverse Distance Weighing) method considering weight of longitude and latitude (Zhuang and Wang, 2003). The set of climate-ecology specific parameters was divided into three regions according to geographic belt distribution of winter wheat varieties in North China (Collaborate Group by Crop and Forest Climate Compartment in China, 1987; Cui et al., 1991). These three regions represent three different climate ecological zones of winter wheat, denoted by Gucheng, Tai'an, and Zhengzhou Stations, characterized by "strong winter hardiness with semi-arid", "winter hardiness with semi-arid," and "winter hardiness with semi-humid", respectively. Some crop parameters related to temperature are interpolated by IDW method. According to an appropriate temperature index required for winter wheat sowing (Beijing Agricultural University Agrometeorological Speciality, 1982), spatial distribution of sowing date was estimated on each grid by using measured temperature in study year.

3.3 *Adjustment of SAIL-PROSPECT model*

The SAIL model, a one-dimensional radiative transfer model, describes the ascending and descending fluxes of direct and diffuse radiation in an absorbing, diffusing and infinite homogeneous layer. The PROSPECT model is a radiative transfer model for individual leaves. The PROSPECT and SAIL models were coupled by leaf reflectance and transmittance. In the study, some parameters of SAIL-PROSPECT model were adjusted by sensitivity analysis and physical characteristics. The LAI-NDVI curve simulated by the calibrated SAIL-PROSPECT model was close to the observed results (Zhang, 1996).

3.4 *The selection of compared object in the course of optimization*

The comparison of simulated outputs and the results retrieved by remote sensing data is a bridge of linking crop model and remote sensing information. The reflectance in different spectral band is generally taken as compared objects. However, vegetation indices show better sensitivity than individual spectral bands for green vegetation detection. NDVI is widely used in vegetation indices, but it is seriously affected by sensor viewing conditions, solar illumination geometry, soil moisture, color, and brightness. Perpendicular vegetation index (PVI) (Richardson and Wiegand, 1977), soil adjusted vegetation index (SAVI) (Huete, 1988), and transformed soil adjusted vegetation index (TSAVI) (Baret and Guyot, 1991) all reduce effects of soil brightness on LAI estimation, and the latter two are better than the former. In the present study, the SAVI was selected as the compared object in the course of optimization owing to its convenience of calculation. The SAVI for each pixel was calculated using red and NIR reflectance as follows:

$$SAVI = [(\rho_n - \rho_r)/(\rho_n + \rho_r + L)](1 + L),$$

where ρ_r and ρ_n are canopy red and NIR reflectances, respectively. L is the adjusted soil coefficient equal to 0.5 for crop cover with medium density.

3.5 *Spatial scale transition of MODIS data*

Compared with SAVI calculated from MODIS data (250 m), the resolution of crop model regionalization is still low (25 km). Therefore, two scales need to transfer in order to match each other. However, it is inappropriate to directly scale up by resampling method owing to great difference of these two resolutions. In the study, three kinds of resolution reflectance (0.25, 2.5, and 25 km) were acquired from MODIS image using resampling methods. Then, different grid reflectances were tested and selected from those three kinds of data to retrieve LAI by SAIL-PROSPECT model. And finally, the appropriate resolution for reflectance images used in this study was determined by comparing retrieved LAI with observed LAI.

3.6 *FSEOPT program*

The FSEOPT, an iterative procedure, uses Price algorithm (Price, 1979) or Downhill-Simplex method to search for the prior values of some parameter vectors within a range through minimizing a cost function $QT(l)$ (also called goodness of fit value):

$$QT'(l) = I\sqrt{\sum_{k=1}^{n} \mid (\frac{d_{lk} - m_{lk}}{d_{lk} - 10^{-8}}) \mid^{I}}, \ (I = 1, 2),$$

$$QT = \max\{QT'(l), l = 1, 2, 3\},$$

where l is state variable, such as LAI, weight of above-ground dry matter, or weight of storage organ. Variables d_{lk} and m_{lk} represent the experimental data and model output, respectively, and k is the number of data points over time for the lth state variable. Variable n is the number of experimental data. I is an optional switch which makes it possible to choose between the sum of absolute residuals (I=1) of the square root of the sum of squares of residuals ($I = 2$). QT denotes maximum under using different state variable. Variable $\overline{Q}$ denotes average QT during development stage.

$$\overline{Q} = QT/n.$$

3.7 *Re-initialization*

Apart from temperature, the sowing date is related to soil moisture and the farmer's cultural practices, and varies a lot in a region. Therefore, the spatial distribution of sowing date estimated according to interpolated temperature may be different from the actual one. This will result in inaccuracy of simulation for emergence. In addition, a sensitivity analysis showed that emergence date had important effect on phenological development and accumulation of biomass. Therefore, the re-initialization of the crop model using remote sensing data was applied to emergence date in the study.

There is a long period of over-winter for winter wheat in North China and it is especially prominent in the north and middle of North China. If it is cold, biomass at turn green stage will decrease dramatically by freezing. This situation results in different spatial distribution of gross dry matter weight above ground at turn green stage for winter wheat. Sensitivity analysis showed that this variable had an important effect on crop growth. However, the WOFOST model fails to simulate this descendent trend of biomass. The re-estimation of biomass at turn green stage aimed at correcting any over-estimation of dry matter cumulation at the end of the winter.

The run flow of WSPFRS model is as follows: the WOFOST-SAIL-PROSPECT model is firstly run to simulate $SAVI_s$ of canopy. And then, initial variables or parameters are re-estimated by minimizing the difference of $SAVI_s$ and $SAVI_m$ observed by remote sensing data. Finally, the crop growth and development are simulated by optimized WOFOST model.

4. Validations of WSPFRS model

Validations of WSPFRS model include the test of accuracy of re-estimating initial variables, parameters themselves and the test of simulated results as well. Firstly, validations were carried out in local sites using field observed data under optimal soil water conditions. Then, the simulation ability of this model was validated at regional scale. Consistency of spatial distribution for simulated and observed phenological stage and biomass was especially investigated.

4.1 *Validation of WSPFRS model in local sites*

The simulations using the WSPFRS model were compared with those outputs from WOFOST model. The day of the year (DOY) of actual emergence date for winter wheat is Day 308 in Zhengzhou in 2002. A range of assumed emergence dates has been applied, from 20 days before to 12 days after actual date, in steps of 5 days. This led to differences in anthesis date from 10 days earlier to 4 days later, and to differences in maturity date from 5 days earlier to 2 days later than the actual date when the WOFOST model simulations (Table 1) were taken. If each assumed emergence date was re-initialized by the WSPFRS model, the value of emergence date could be relocated more closely to the actual one. Table 1 shows clearly that the bias of the optimized emergence date (as compared

Table 1. Errors of simulated winter wheat development stage by WSPFRS and WOFOST models (Zhengzhou, 2002-2003)

Emergence (day)		Anthsis (day)		Maturity (day)	
WOFOST	WSPFRS	WOFOST	WSPFRS	WOFOST	WSPFRS
-33	16	-	-	-	-
-20	4	-10	1	-5	1
-15	0	-6	0	-3	0
-10	-2	-4	-1	-2	-1
-5	-5	-2	-1	-1	-1
0	-3	0	-1	0	-1
5	-2	2	-1	1	-1
10	3	3	2	2	1
12	4	4	1	2	1

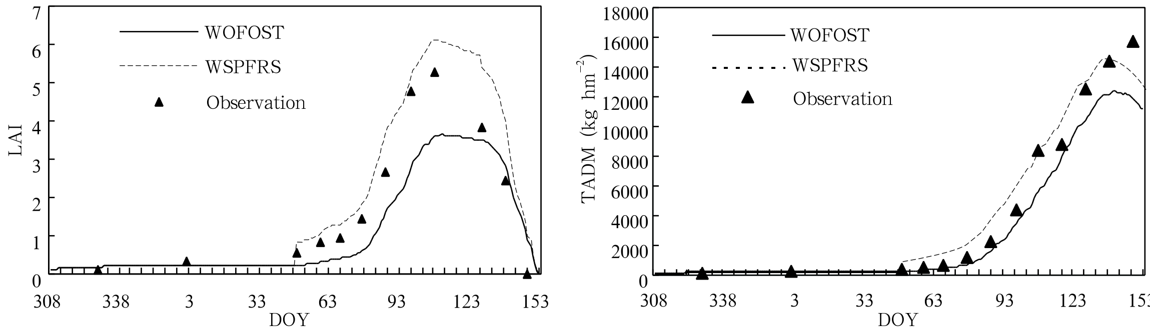

Fig.2. LAI (a) and total above-ground dry matter weight (TADM, b) of winter wheat simulated by WSPFRS model and WOFOST model compared with observed values (Zhengzhou, 2002-2003).

to the actual one) reduced to within 5 days in case of 20-day difference between assumed and actual date. As a consequence, the simulated anthesis date and maturity date showed very good agreement with the simulation using actual emergence date.

Winter wheat growth during the growing season from 2002 to 2003 in Zhengzhou was simulated by WSPFRS and WOFOST models, respectively (Fig. 2). In WSPFRS simulation, the biomass at turn green stage was re-estimated by using a time series of seven MODIS images collected in the period from turn-green to maturity stage. The results showed that the relative error of simulated maximum LAI was reduced from 31.7% using WOFOST model to 15.8% using WSPFRS model, and the relative error of simulated total above-ground dry matter weight decreased from 24.4% to 15.3%. These results illustrate that the WSPFRS model has great potential for winter wheat simulation compared with WOFOST model.

4.2 *Validation of WSPFRS model on regional scale*

4.2.1 *Validation of simulated phenological stage on regional scale*

Sowing dates were estimated according to an appropriate temperature index and then WOFOST model was run to acquire emergence date over the entire region of North China in 2002 (Fig.3a). Then, the emergence date was re-initialized by the WSPFRS model using 11 images of SAVI calculated from MODIS data (Fig.3b). The results showed that re-initialized emergence date brought forward about 10 days in most areas of North China. In fact, this situation was closer to actual emergence date observed by 48 agrometeorological stations (Fig.3c) in middle and southern parts of North China. However, large errors existed in northern part of North China because of the big difference of sowing dates in climate and actual values.

Figures 3d and 3e are the simulated turn green date and corresponding development stage (DVS) by WSPFRS model. It showed that the turn green phase occurred in turn of time from southern to northern of North China. The earliest turn green stage was about Day 43 of DOY and corresponding DVS was 0.20 in southern part while the latest was about Day 75 of DOY and corresponding DVS is 0.45 in northern part. This was basically consistent with observations in most areas of North China but obvious errors in west of Henan Province, which may result from lack of observations (Fig.3f).

Figure 4 is simulated anthesis and maturity dates (in terms of DOY) of winter wheat respectively by WSPFRS and WOFOST models in North China in 2003. It is seen that maturity simulated by WSPFRS is advanced after adjusting using remote sensing data compared with WOFOST simulations in most areas of Henan Province, south of Hebei Province, and west of Shandong Province as well. According to observations from the national agrometeorological service department, in this year, the spiking stage of winter wheat is from Days 101-110 of DOY in southern part of North China to Days 121-130 of DOY in northern parts, then maturated from Days 152-161 of DOY to

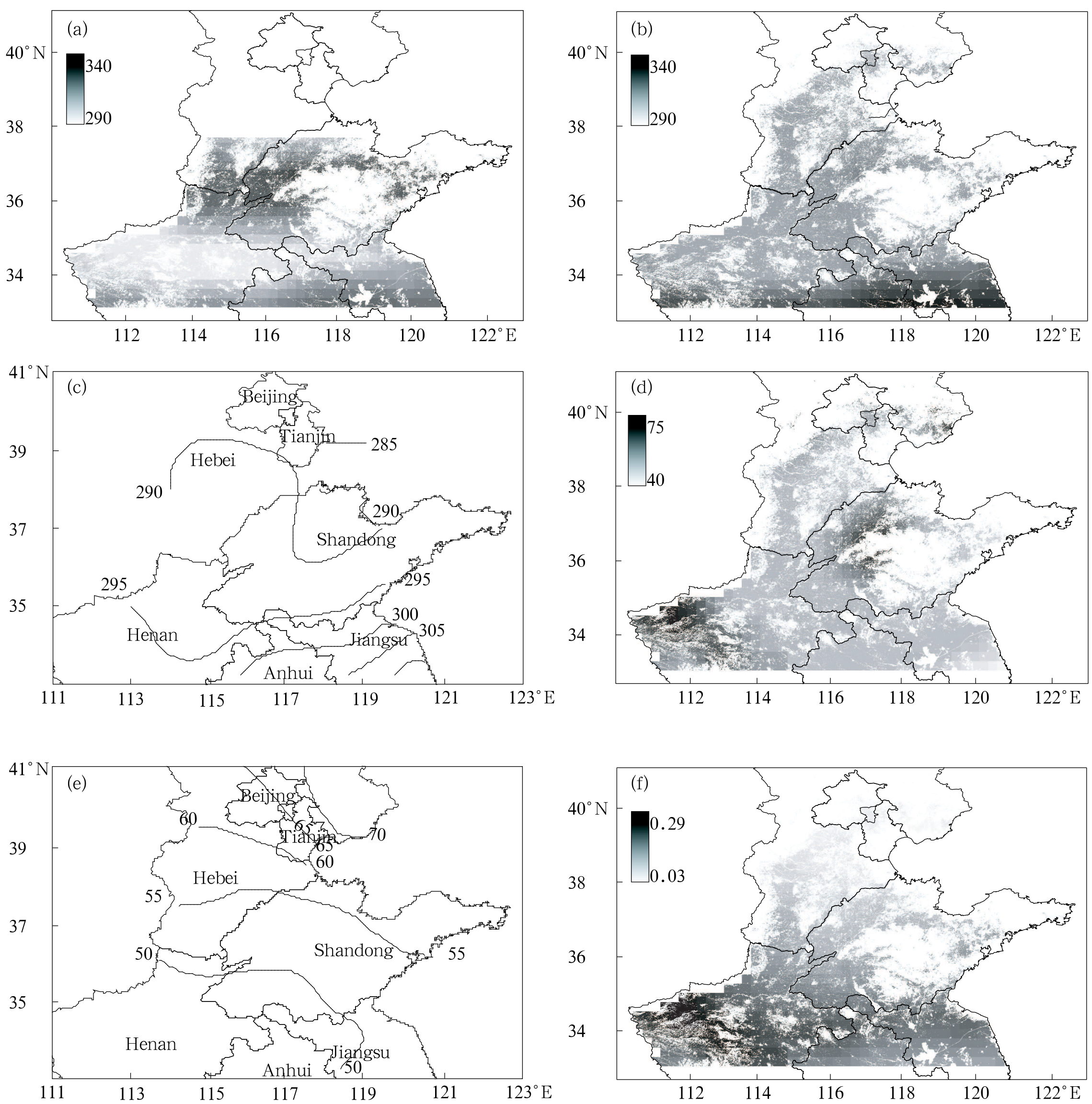

Fig.3. Simulated and measured emergence date (in terms of DOY), turn-green date in terms of DOY and DVS at turn-green date for winter wheat in North China in 2002. (a) Emergence date simulated by WOFOST, (b) emergence date adjusted by WSPFRS model, (c) measured emergence date, (d) turn-green date simulated by WSPFRS model, and (e) measured turn-green date; unit: day.

Days 162-171 of DOY (Fig.4). This was more consistent with WSPFRS model simulations than WOFOST.

4.2.2 *Validation of growth simulation on regional scale*

The WOFOST model was firstly run to simulate biomass at turn green stage of winter wheat over the entire region in 2003 (Fig.5a). Then, this biomass was re-estimated by WSPFRS model using seven SAVI images (Fig.5b). The results showed that re-estimated biomass at turn green stage was lower in most areas of North China Plain than simulations using WOFOST model, while there was increasement in Zhumadian in the south of this plain. This new spatial distribution of biomass after over-winter in different region was quite consistent with the actual situation, which implies the dormancy from cold in northern parts and slow growth in southern parts. It can be seen that remote sensing

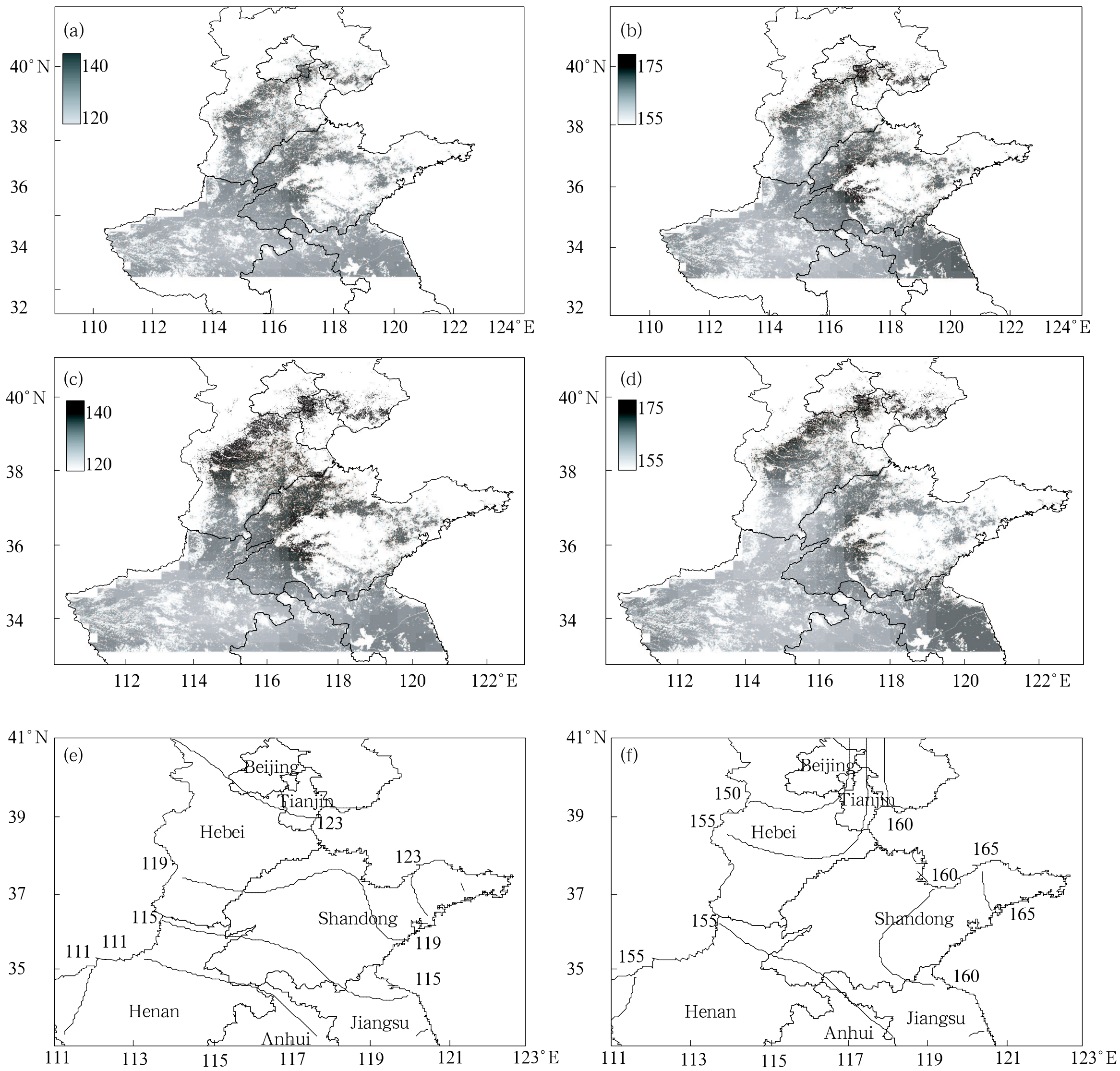

Fig.4. Simulated and measured anthesis and maturity dates (in terms of DOY) of winter wheat in North China in 2003. (a) and (b) denote anthesis and maturity dates simulated by WOFOST; (c) and (d) denote anthesis and maturity date simulated by WSPFRS model; and (e) and (f) denote measured spiking and maturity date.

data play a role in adjusting biomass at turn green stage.

The gross above-ground dry matter weight of winter wheat simulated by WSPFRS model was reduced compared with WOFOST simulation in North China in 2003 (Fig.6), which was attributed to the re-estimation of biomass at turn green stage using remote sensing data.

Simulated WSO (Weight of storage organ) using WSPFRS model decreased from 2500 kg hm^{-2} to 0 compared with the simulated WSO using WOFOST model, especially reduced a lot in Henan Province (see Fig.7). The average WSO values using WOFOST model in Shandong, Henan, and Hebei Provinces were aggregated from grids, which were 8632.7, 7641.1, and 6128.7 kg hm^{-2}, respectively. These values were about equidistant descending. However, aggregated average WSO values with WSPFRS model correspondingly were 8052.0, 6189.1, and 5951.9 kg hm^{-2}, respectively. The values in Henan and Hebei Provinces were quite

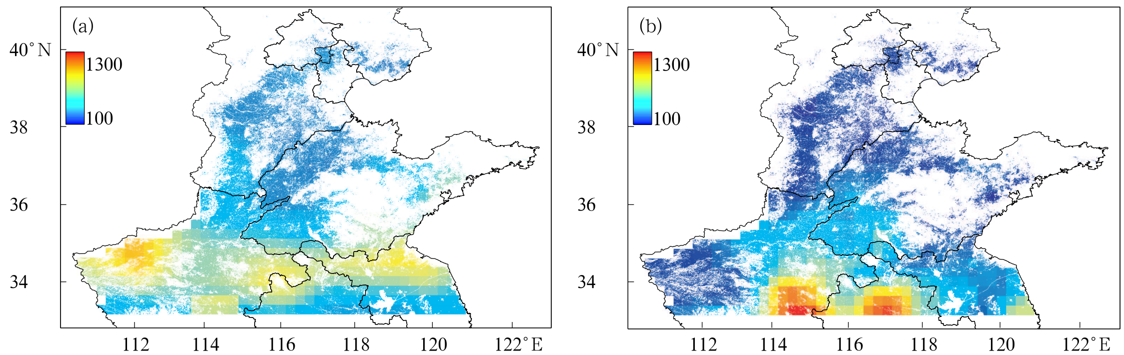

Fig.5. Simulated biomass of winter wheat at turn-green stage in North China in 2003. (a) WOFOST and (b) WSPFRS, unit: kg hm^{-2}.

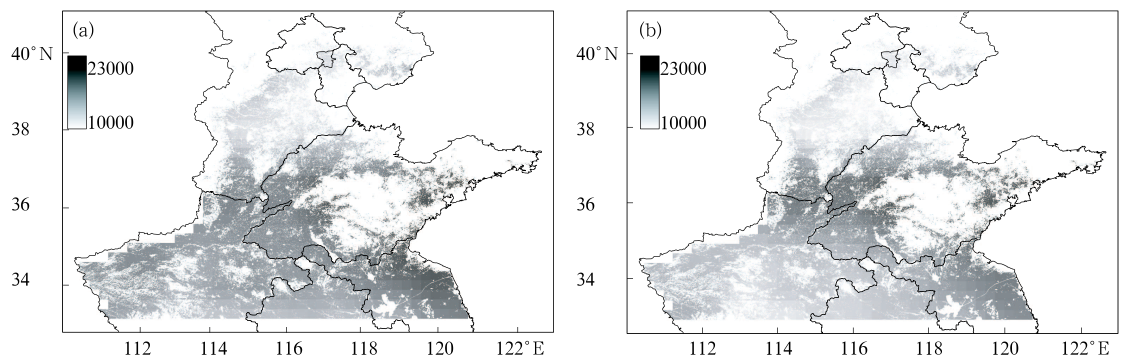

Fig.6. Simulated gross above-ground dry matter weight of winter wheat in North China in 2003. (a) WOFOST and (b) WSPFRS, unit: kg hm^{-2}.

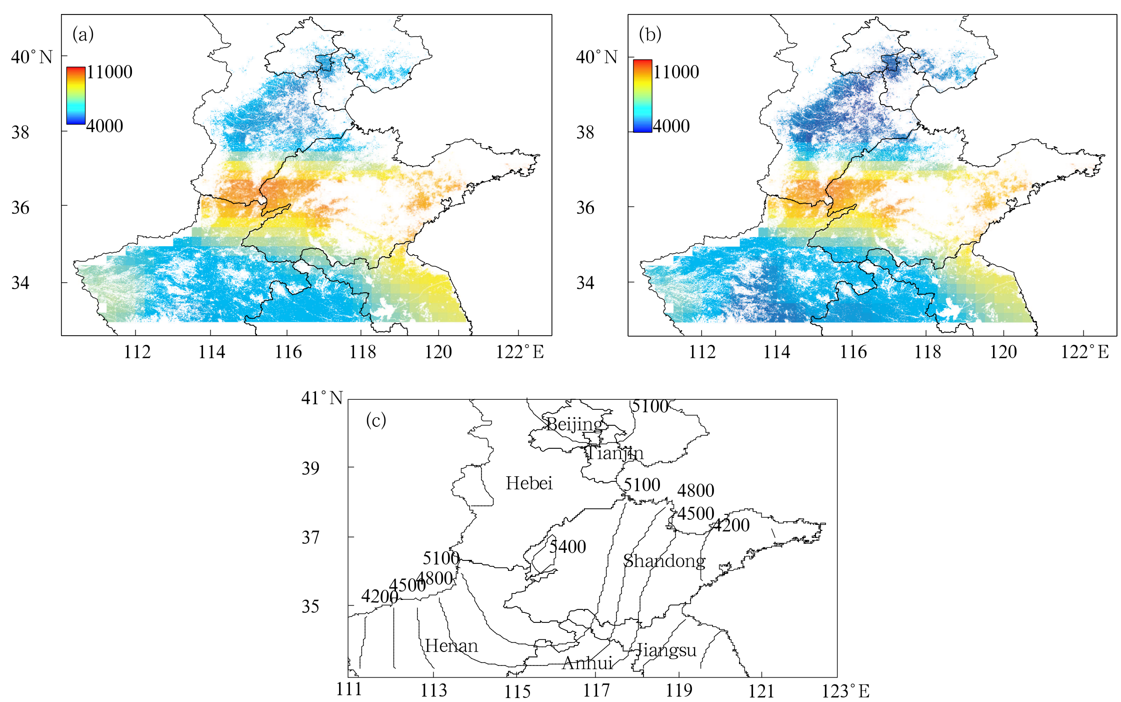

Fig.7. Simulated WSO and measured yields of winter wheat in North China in 2003. (a) WOFOST, (b) WSPFRS, and (c) measured yields. Unit: kg hm^{-2}.

close while there were higher values in Shandong Province. The same situation could be found from official yields, which were correspondingly 5040.1, 4771.5, and 4643.3 kg hm^{-2}. Because of the high correlation relationship of storage organ weight and yields, we can say that the spatial distribution of simulated results for WSPFRS model by assimilating remote sensing data was more consistent official yields than results without remote sensing data. In addition, the area of highest values area (above 9000 kg hm^{-2}) for simulated WSO with WSPFRS model was located in the middle of North China, especially in west of Shandong Province, north of Henan Province, and south of Hebei Province. This region was similar to the distribution of high values of official yields. It indicated that the area with high values of WSO nearly consisted to the actual high yield area.

5. Conclusions and discussions

In this paper, the method of coupling crop model and remote sensing data using assimilation strategy was investigated. A regional remote sensing crop simulation framework model (WPSFRS model) was established in potential production level. Some major conclusions are as follows:

(1) After some inheritance parameters under potential production level were adjusted for winter wheat in North China using field observed data, the WOFOST model well simulates the growth and development of winter wheat. Based on the interpolation of weather data, regionalization of crop parameters and initial conditions and spatial scale matching of crop model and remote sensing data, the WOFOST model can be applied in regional scale.

(2) Based on coupling the SAIL-PROSPECT model to crop model through the state variable LAI, the WOFOST model was re-initialized/reparameterized by SAVI calculated from MODIS data. Thus, a mechanistic regional remote sensing crop simulation framework model (WSPFRS) has been established in potential production level (optimal soil water condition).

(3) The emergence date and biomass at turn-green stage were re-initialized or re-estimated over a large area using MODIS data owing to scarcity of spatial information. The WSPFRS model gave better estimates of the phenological stage and accumulation of biomass for winter wheat. After re-initializing regional emergence date, anthesis and maturity dates simulated by WSPFRS model were more close to measured values than simulated results of WOFOST. Owing to re-estimation of regional biomass weight at turn-green stage, spatial distributions of simulated storage organ weight were more consistent with measured yields and the area with high values nearly consisted to the area of actual high yields. The results demonstrated that such an approach was helpful for scaling the local simulation of crop model up to the regional scale.

(4) There are still some issues requiring more attentions owing to complex interdiscipline involving agronomy, geoscience and remote sensing technique as well as lack of data. Such an adaptation and regionalization of crop model requires more details including data observed at field plots. Remote sensing data should be processed accurately for geometric, radiometric, and atmospheric corrections. Canopy radiative transfer model should minimize the errors in the estimates of canopy parameters using more remotely sensed and field observed data, so as to improve its accuracy. In the present study a test was carried out how the differences in spatial resolutions applied in remote sensing and in crop modeling could be matched or bridged, but more discussions and experiments are needed in appropriate resolutions and strategies in scaling-up or downscaling.

(5) In the paper, an assimilation process in potential production level was developed and a case of winter wheat growing season from 2002 to 2003 under basically optimal soil moisture conditions was presented. Further work will concern about how to combine more remotely-sensed information to simulate phenological development and growth for winter wheat at water limited production level.

(6) Feasibility of re-estimating emergence and biomass at turn green stage was studied in this paper. There are other parameters, such as maximum growth rate of LAI in early stage and senescence factor of

leaves, which also should be considered to re-estimate in the further study.

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