Uncertainty from model structure is larger than that from model parameters in simulating rice phenology in China

Shuai Zhang^a, Fulu Tao^{a,c,*}, Zhao Zhang^b

^a Key Laboratory of Land Surface Pattern and Simulation, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China

^b State Key Laboratory of Earth Surface Processes and Resource Ecology, Beijing Normal University, Beijing 100875, China

^c Natural Resources Institute Finland (Luke), FI-00790 Helsinki, Finland.

*Correspondance: Fulu Tao. E-mail: taofl@igsnrr.ac.cn

Abstract. Rice models have been widely used in simulating and predicting rice phenology in contrasting climate zones, however the uncertainties from model structure (different equations or models) and/or model parameters were rarely investigated. Here, five rice phenological models/modules (i.e., CERES-Rice, ORYZA2000, RCM, Beta Model and SIMRIW) were applied to simulate rice phenology at 23 experimental stations from 1992 to 2009 in two major rice cultivation regions of China: the northeastern China and the southwestern China. To investigate the uncertainties from model biophysical parameters, each model was run with randomly perturbed 50 sets of parameters. The results showed that the median of ensemble simulations were better than the simulation by most models. Models couldn't simulate well in some specific years despite of parameters optimization, suggesting model structure limit model performance in some cases. The models adopting accumulative thermal time function (e.g., CERES-Rice and ORYZA2000) had better performance in the southwestern China, in contrast, those adopting exponential function (e.g., Beta model and RCM model) had better performance in the northeastern China. In northeastern China, the contribution of model structure and model parameters to model total variance was, respectively, about 55.90% and 44.10% in simulating heading date, and about 75.43% and 24.57% in simulating maturity date. In the southwestern China, the contribution of model structure and model parameters to model total variance was, respectively, about 79.97%

and 27.03% in simulating heading date, about 92.15% and 7.85% in simulating maturity date. Uncertainty from model structure was the most relevant source. The results highlight that the temperature response functions of rice development rate under extreme climate conditions should be improved based on environment-controlled experimental data.

Keywords: crop model; extreme weather; impacts; rice development rate; uncertainty

1. Introduction

Crop phenology is closely related to agricultural system dynamic and crop yield, hence, it is important to understand and predict crop development and phenology (Bradley et al., 1999; Abu-Asab et al., 2001; Zhang et al., 2004; White et al., 2009). Crop phenological models are routinely applied to simulate and predict crop development and phenology (Zhang and Tao, 2013, 2014; Timsina and Humphreys et al., 2006; Palosuo et al., 2011). Although great progress in crop modelling has been made in last decades, crop phenological models have still large uncertainties (Rötter et al., 2011; Zhang and Tao, 2013; Asseng et al., 2013; Bassu et al., 2014; Li et al., 2015). Crop phenological models are various in describing the response of crop development as a function of temperature, daylength and vernalization (Jones et al., 2003; Kropff et al., 1995; Bouman et al., 2001). Some of them adopt an accumulative thermal time function and some of them adopt an exponential function in simulating the response of crop development to temperature. The CERES-Rice, ORYZA2000, Rice Clock Model (RCM), Beta Model and Simulation Model for Rice-Weather relationship (SIMRIW) are widely used, easily accessible and well-documented rice growth simulation models (Matthews et al., 1997; Yin et al., 1997; Mahmood, 1998; Jin et al., 2003; Das et al., 2007; Chen et al., 2008). These models show rice development rate increases with temperature but with different development rates (Zhang and Tao, 2013). Most previous studies try to estimate the optimal parameters of existing models to reduce model errors (Challinor et al., 2005; Iizumi et al., 2009; Tao et al., 2009). However, the rice development rate is not only related to model parameters, but also depends largely on model structure (the form of the equation) (He et al., 2014). In fact, because different rice models employ different functions to simulate the response of rice development rate to temperature, the simulated rice development rate varies largely among these models (Zhang and Tao, 2013). To reduce model errors, it is necessary to investigate the roles of model parameters and model structure in causing model errors.

In the present study, we intend to investigate the sensitivity of crop development rate to model biophysical parameters and model structure using the five rice phenological models. We aim to (1) investigate the uncertainty of phenological simulation from model biophysical parameters in each of the five models; (2) investigate the uncertainty of phenological

simulation from different phenological models (model structure); (3) compare the relative contribution of model structure and model biophysical parameters to model total variance.

2. Materials and Methods

2.1. Observed rice phenology and climate data

We focused on the single-season rice cultivated in the northeastern China (zone I) and southwestern China (zone II) (Fig. 1). Observed rice phenology data and daily weather data were obtained from 23 national agro-meteorological experiment stations (11 stations in zone I and 12 stations in zone II), managed by China Meteorological Administration (CMA).

For all the stations in zone I, the range of maximum temperature was from -28.0 °C to 37.8 °C, with 80% of the values between -1.87 °C and 27.13 °C. The range of minimum temperature was from -44.1 °C to 27.2 °C, with 80% of the values between -18.9 °C and 17.0 °C. The frequency distribution of temperatures during rice growth season in zone I was shown in Fig. 2. The range of temperatures was from 3 °C to 31 °C, and the peak value was 21 °C. For all the stations in zone II, the range of maximum temperature was from -3.4 °C to 43.2 °C, with 80% of the values between 12.7 °C and 33.7 °C. The range of minimum temperature was from -12.1 °C to 31.4 °C, with 80% of the values between 5.6 °C and 23.7 °C. The range of temperature was from 4 °C to 35 °C, and the peak value was 26 °C (Fig. S1).

For each station, the dates of the major phenological events were recorded by local agro-technicians. The choice of rice cultivars was based on the major cultivar used by local farmers in the investigating year. Rice cultivars were usually renewed for every three to five years (Zhang et al., 2012). Observed rice transplanting date, heading date and maturity date for each station from 1992 to 2009, as well as the datasets of daily and monthly mean temperature, at these stations were used. In this study, the phenological data from 1992 to 2000 at each station were used to calibrate the parameters of all five models and those from 1992 to 2009 were employed to evaluate the models.

2.2. Descriptions of the rice phenology models

Five widely used, easily accessible and well-documented rice growth simulation models, i.e. CERES-Rice, ORYZA2000, RCM, Beta Model and SIMRIW, were applied in this study. Each model used different parameters and methods to simulate rice development rate. In order to compare these five models, we unified the growth stage in these models. The stage from transplanting date to heading date was defined as vegetative growth period (VGP); the stage from heading date to maturity date was defined as reproductive growth stage (RGP). The developmental index (DVI) was defined as 0.1 at transplanting, 1.0 at heading and 2.0 at maturity. Therefore, DVI of VGP was from 0.1 to 1.0, and DVI of RGP was from 1.0 to 2.0. The value of DVI was calculated by summing the developmental rate (DVR) with respect to time:

$$DVI_t = \sum_{i=0}^{i=t} DVR_i \quad (1)$$

where DVI_t is the developmental index at day t , and DVR_i is the developmental rate on the i -th day from transplanting. Models are described briefly below.

The CERES-Rice model (Alocija & Ritchie, 1988; Jones et al., 2003) has been used extensively to simulate rice growth and yield over a wide range of environments, including China (Tao et al., 2008; Xiong et al., 2008). The version we used was a modified version as Li et al. (2015). In this version, daily thermal time (DTT) is used to describe the process of rice development. VGP completes when the accumulation of DTT reaches a threshold (P1); RGP completes when the accumulation of DTT reaches a threshold (P5). The equations can be converted as follows:

$$DVR = DTT \cdot FDL / P1 \quad \text{for} \quad 0 < DVI \leq 1 \quad (2)$$

$$DVR = DTT / P5 \quad \text{for} \quad 1 < DVI \leq 2 \quad (3)$$

DTT is calculated as follows:

$$\begin{cases} DTT_i = 0 & \text{for } T_{\max} \leq T_{base} \text{ or } T_{\min} \geq T_{high} \\ DTT_i = (T_d - T_{base}) / 24 & \text{for } T_{\max} > T_{opt} \text{ or } T_{\min} < T_{base} \\ DTT_i = (T_{\max} + T_{\min}) / 2 - T_{base} & \text{for others} \end{cases} \quad (4)$$

where T_{opt} is the optimum temperature, T_{high} is a critical high temperature for crop development, T_{base} is the base temperature. $T_{\min}$ and $T_{\max}$ are the daily minimum and maximum temperatures. T_d is hourly temperature. h is the hour of the day. T_d is calculated by $T_{\min}$ and $T_{\max}$:

$$T_d = (T_{\min} + T_{\max}) / 2 + (T_{\max} - T_{\min}) / 2 \cdot \sin[3.14 / 12 \cdot h] \quad (5)$$

$$\begin{cases} T_d = T_{base} & \text{for } T_d < T_{base} \\ T_d = T_{opt} - (T_d - T_{opt}) & \text{for } T_d > T_{opt} \end{cases} \quad (6)$$

Day length (FDL) is calculated as follows:

$$FDL = [1 + P2R/136 \times (DL_k - DL_c)]^{-1} \quad (7)$$

where DL_k is daily mean day length. DL_c is the critical day length. $P2R$ is photoperiod sensitivity parameter.

In the ORYZA2000 (Kropff et al., 1995; Bouman et al., 2001) model, daily increments in developmental time (DTU) is used to describe rice development. VGP completes when the accumulation of DTU reaches a threshold (DVRI); RGP completes when the accumulation of DTU reaches another threshold (DVRR). The equations can be converted as follows:

$$DVR = DTU \cdot FDL / DVRI \quad \text{for } 0 < DVI \leq 1 \quad (8)$$

$$DVR = DTU / DVRR \quad \text{for } 1 < DVI \leq 2 \quad (9)$$

DTU is calculated as:

$$DTU = \sum_{h=1}^{24} (HD) \quad (10)$$

$$\begin{cases} HD = 0 & \text{for } T_d \leq T_{base} \text{ or } T_d \geq T_{high} \\ HD = (T_d - T_{base}) / 24 & \text{for } T_{base} < T_d \leq T_{opt} \\ HD = [T_{opt} - (T_d - T_{opt}) \times (T_{opt} - T_{base}) / (T_{high} - T_{opt})] / 24 & \text{for } T_{opt} < T_d < T_{high} \end{cases} \quad (11)$$

where HD is hourly increments in developmental age. T_d is calculated from T_{min} and T_{max}

as:

$$T_d = (T_{min} + T_{max}) / 2 + (T_{max} - T_{min}) / 2 \cdot \cos[0.2618(h-14)] \quad (12)$$

FDL is calculated as:

$$FDL = 1 - (DL_k - DL_c) \times PPSE \quad (13)$$

where PPSE is photoperiod sensitivity parameter.

The RCM (Gao, 1992) describes a base model covering the entire stage of rice development and uses daily mean temperature and day length data to calculate rice daily development rate.

$$DVR = \exp(k) \left(\frac{T - T_{base}}{T_{opt} - T_{base}} \right)^P \left(\frac{T_{high} - T}{T_{high} - T_{opt}} \right)^Q \exp[G(DL_k - DL_c)] \quad (14)$$

$$\begin{cases} T = T_{base} & \text{for } T < T_{base} \\ T = T_{high} & \text{for } T > T_{high} \end{cases} \quad (15)$$

$$DL_k = DL \quad \text{for } DL_k < DL_c \quad (16)$$

where T is the daily mean temperature, k , P , Q and G are empirical constants, during RGP, $G = 0$ is assumed.

The nonlinear Beta model (Yin et al., 1995; Yin and Kropff, 1996) is described as:

$$DVR = \exp(\mu)(T - T_{base})^\alpha (T_{high} - T)^\beta \cdot DL_k^\delta (24 - DL_k)^\varepsilon \quad \text{for } 0 < DVI \leq 1 \quad (17)$$

$$DVR = \exp(\mu)(T - T_{base})^\alpha (T_{high} - T)^\beta \quad \text{for } 1 < DVI \leq 2 \quad (18)$$

where μ , α , β , δ and ε are empirical constants.

In the SIMRIW (Horie, 1995), the phenological development is described by using the Developmental Index (DVI). DVR from transplanting to heading ($0 < DVI < 1$) is calculated as follows:

$$\begin{cases} DVR = \{1 - \exp[B(DL_k - DL_c)]\} / G_v \{1.0 + \exp[-A(T - T_h)]\} & \text{for } DL_k \leq DL_c \\ DVR = 0 & \text{for } DL_k > DL_c \end{cases} \quad (19)$$

where T_h is the temperature at which DVR is half the maximum rate at the optimum

temperature ($^{\circ}\text{C}$), G_v is the minimum number of days required for heading, A and B are empirical constants.

The following equation is used to describe the rate of rice development from heading to maturity ($1 < DVI \leq 2$)

$$DVR = \{1 - \exp[-K_r(T - T_{cr})]\} / G_r \quad (20)$$

where G_r is the minimum number of days for grain-filling period K_r and T_{cr} are empirical constants.

2.3. Parameter perturbation

To better understand the uncertainty from model parameters, the runif function in R software was used to randomly perturb model parameters. The parameters of the five models were calibrated by minimizing the following cost function:

$$J(x) = \frac{1}{n} \sum_i \left(obs_i - m(x) \right)^2 \quad (21)$$

where x is the parameters in rice phenology models. obs_i is the i^{th} measurement. n is the total number of measurements. The cost function presents the mismatches between observations and predictions. A global optimization method named SCE-UA (shuffled complex evolution method) was applied to minimize the cost function (Duan et al., 1994) with Matlab software. 50 sets of model parameters were generated by random sampling method with an assumption that each parameter had a Gaussian distribution. For each parameter, the mean value of the Gaussian distribution was the calibrated value of the parameter. The variance of the Gaussian distribution was the uncertainty of the parameter. Then each of the five phenological models was run with its respective 50 sets of perturbed parameters. One set of optimal parameters and range of 50 sets of perturbed parameters were shown in Table 1.

2.4. uncertainties from model structure and model parameters

The uncertainty from model structure was investigated by comparing the simulations using each of the five crop models with its respective one set of optimal parameters. The uncertainty from model parameters was investigated by comparing the simulations with one set of optimal parameters and 50 sets of perturbed parameters. A super-ensemble simulation was conducted using the five models with their respective 50 sets of perturbed parameters to investigate the uncertainties from both model structure and model parameters.

2.5. Contributions of model structure and model parameters to model total variance

Uncertainty of simulation was used to compare the simulation to observation. As Wallach et

al. (2016), we used the distribution of $y - \hat{f}(X; \hat{\theta})$ to define the uncertainty: y is

predictand, $\hat{f}$ is the applied model structure, X is the input of the model, $\hat{\theta}$ is model

parameter. $\hat{f}$ presents the fixed model. In order to get the contribution of structural uncertainty, we averaged parameters of each model and then calculated the variance

among different models. To obtain the contribution of parameter uncertainty, we calculated the variance of the simulations generated by each model with 50 sets of perturbed parameters and then averaged the variance among all the models. The two parts of model variance were estimated using the simulations with the five models and their respective 50 sets of parameters. Then, the estimation of σ_{τ}^2 (structure uncertainty) and σ_{θ}^2 (parameter uncertainty) was deemed as the problem of variance (Scheffé, 1959; Wallach et al., 2016).

2.6. Analyses

Uncertainties from crop models were evaluated by comparing ensemble simulations with observations. The median of the individual model simulations was used to compare with observations. We evaluated the accuracy of models by calculating the model bias (Bias), root mean square error (RMSE) and Pearson correlation coefficients (r) between the observed and simulated values for both heading date and maturity date. The mismatch between simulations and observations was reduced when the suitable parameters were found. In some cases, performance of models would not be improved by model parameter calibrations. We assume these errors should be largely ascribed to incorrect model structure. Errors not related to model parameters were identified as uncertainties from model structure.

3. Results

3.1. Uncertainties from model structure

Uncertainty from model structure was investigated by comparing the model simulations using each of the five models with its respective one set of optimal parameters. In zone I, with one set of optimal parameters, the highest development rate occurred when temperature approached about 30°C (Fig. 3). For heading date, the simulated highest development rate was about 0.022 by CERES-Rice and ORYZA2000, and 0.016, 0.015, and 0.017 by RCM, Beta model, and SIMRIW, respectively (Fig. 3a). For maturity date, the simulated highest development rate was 0.030, 0.037, 0.026, 0.021, and 0.023 by CERES-Rice, OYRZA2000, RCM, Beta Model, and SIMRIW, respectively (Fig. 3b). The RMSEs ranged from 6.09 to 6.70 days with r from 0.27 to 0.30. RCM model got the least RMSE among all the five models, although it underestimated heading date by 1.89 days. The performance of CERES-Rice and ORYZA2000 was similar in some statistics (Fig. 3, Table 2). The five phenological models with their respective one set of optimal parameters could simulate rice heading date well. However the large errors were found for simulations of heading dates in some specific years (Fig. 4, Fig. S3). For example, in zone I, all models failed to simulate heading date well in 1993, 1998 and 2009 (Fig. 4). CERES-Rice overestimated heading date while other models underestimated heading date. Simulations of maturity date by the five

models were quite different. The RMSEs ranged from 4.33 to 9.12 days (Table 2). All five models got a larger r in simulating maturity date than in simulating heading date (Table 2). RCM, Beta models and SIMRIW got a smaller RMSE in simulating maturity date than in simulating heading date (Table 2).

In zone II, the RMSEs ranged from 7.08 to 8.60 days. CERES-Rice got the least RMSE among all the five models. The bias of simulation of CERES-Rice was 0.20 days, with r ranging from 0.80 to 0.84 (Table 2). For heading date, with one set of optimal parameters, the simulated highest development rate was 0.020, 0.019, 0.014, 0.016, and 0.017 by CERES-Rice, OYRZA2000, RCM, Beta Model and SIMRIW, respectively (Fig. S2a). For maturity date, with one set of parameters, the simulated highest development rate was 0.034, 0.040, 0.034, 0.033, and 0.039 by CERES-Rice, OYRZA2000, RCM, Beta Model and SIMRIW, respectively (Fig. S2b). For single-season rice cultivated in zone II, the heading date was overestimated in 1992. In 1999 and 2001, RCM and Beta model underestimated heading date. For single-season rice cultivated in zone II, RMSEs in simulating maturity date ranged from 4.256 to 5.42 days (Table 2). All the models overestimated heading date in 1994 (Fig. S3).

3.2. Uncertainties from model parameters

Each of the five models was driven by its respective 50 sets of perturbed parameters to investigate the uncertainty from model parameters. The median value of ensemble simulations using each model with its respective 50 sets of perturbed parameters was used to compare with the observation (Table 2). For heading date, the statistics (RMSE, r , Bias) of the ensemble simulations were close to those of the corresponding simulation with one set of optimal parameters. For maturity date, the ensemble simulations with 50 sets of perturbed parameters were better.

In zone I, with 50 sets of perturbed parameters (Fig. 5), for heading date, the simulated highest development rate was 0.022-0.025, 0.022-0.024, 0.015-0.016, 0.014-0.016, and 0.017-0.018 by CERES-Rice, OYRZA2000, RCM, Beta Model, and SIMRIW, respectively (Fig. 5a). For maturity date, the simulated highest development rate was 0.030-0.032, 0.036-0.040, 0.024-0.028, 0.020-0.025, and 0.021-0.024 by CERES-Rice, OYRZA2000, RCM, Beta Model, and SIMRIW, respectively (Fig. 5b). Simulations from CERES-Rice model with one set of optimal parameters close to observation except the simulations in 1993, 1998 and 2009 (Fig. 4). There were still some errors in heading date and maturity date simulations even using the ensemble simulations with 50 sets of perturbed parameters, (Fig. 6a). In 1993, 1994, 1995, 1999, 2000, and 2009, CERES-Rice couldn't simulate rice maturity date reasonably well (Fig. 6a). Likewise, OYRZA2000 simulated heading date better than maturity date (Fig. 6b). In 1993, 1994, 2000, 2005, and 2008, the RMSE of maturity date simulation was larger. All the models underestimated heading date. Beta model has good performance

in maturity date simulations (Fig. 6c, d). Ensemble simulations of Beta model and ORYZA2000 with their respective 50 sets of perturbed parameters performed better, suggesting model parameters optimization could improve the performance of the two models in simulating maturity date. However, the model errors in simulating heading dates couldn't be improved obviously by optimizing model parameters. SIMRIW performed well on simulating heading date and maturity date (Fig. 6e).

In zone II, for heading date, with 50 sets of parameters, the simulated highest development rate was 0.019-0.021, 0.018-0.019, 0.013-0.015, 0.015-0.018 and 0.015-0.017 by CERES-Rice, OYRZA2000, RCM, Beta Model, and SIMRIW, respectively (Fig. S4a). For maturity date simulation, the simulated highest development rate was 0.032-0.035, 0.038-0.041, 0.030-0.036, 0.031-0.035, and 0.036-0.040 by CERES-Rice, OYRZA2000, RCM, Beta Model, and SIMRIW, respectively (Fig. S4b). The ensemble simulations with 50 sets of perturbed parameters also reduced model errors slightly, in comparison with the simulations with one set of optimal parameters. For example, the CERES-Rice model with its 50 sets of perturbed parameters overestimated heading dates from 1992 to 1996 (Fig. S5a). OYRZA2000 and RCM model were improved by the ensemble simulations (Fig. S5b, c). The results from all the five models indicated that ensemble simulations with their respective 50 sets of perturbed parameters could only improve model performance slightly if the models were well calibrated (Fig. S5). In other words, the uncertainty from model parameters should be less than that from model structure.

3.3. Super-ensemble simulations with the five models and 50 sets of perturbed parameters

The median of super-ensemble simulations with the five models and their respective 50 sets of perturbed parameters were better than simulations by most of the models with their respective one set of optimal or 50 sets of perturbed parameters, for both heading date and maturity date (Table 2).

In zone I, for heading date, all models had similar simulations (Fig. 7). SIMRIW model got the best estimates among all the five models. All five models underestimated heading date. RCM and Beta model underestimated more than other models, which may be ascribed to model structure because RCM and Beta models have similar model structure (exponential function). For maturity date, the simulations with the five models were quite different. OYRZA2000 had the best estimates among the five models. RCM overestimated maturity date most.

In zone II, OYRZA2000 got the best estimate of heading date, RCM and Beta model underestimated heading date (Fig. S6). Most models overestimated maturity date before 1998, the simulation of maturity date was better after 1998 than before 1998. The super-

ensemble simulation with the five models and their respective 50 sets of perturbed parameters could not improve the simulations in several years.

3.4. Contributions of model structure and model parameters to model variance

Share of the model total variance from model structure and model parameters in simulating heading date and maturity date was investigated. In zone I, the results showed that the contribution of model structure to model total variance was 26.21% to 93.98% in simulating heading date (Fig. 8a), and 38.97% to 97.31% in simulating maturity date (Fig. 8b). In contrast, the contribution of model parameters was 6.02% to 73.79% in simulating heading date (Fig. 8a), and 2.69% to 61.03% in simulating maturity date (Fig. 8b). In zone II, the results showed that the contribution of model structure to model total variance was 71.63% to 86.73% in simulating heading date (Fig. S7a), and 90.14% to 97.61% in simulating maturity date (Fig. S7b). In contrast, the contribution of model parameters was 15.36% to 28.37% in simulating heading date (Fig. S7a), and 2.39% to 9.52% in simulating maturity date (Fig. S7b).

4. Discussion

Robust model parameterization based on observed data is essential and pre-requirement for model applications. To quantify the uncertainties in model simulation and climate change impact assessment, ensemble simulations have been widely recommended (Tao et al., 2009a, b, Asseng et al., 2013, Martre et al., 2015). The ensemble simulations from 27 wheat models indicated that the median values of ensemble simulations had better performance than any individual simulations (Asseng et al., 2013; Martre et al., 2015). Our results also indicated that the median values of ensemble simulations were more accurate than most individual simulations (Table 2). The possible explanation is that the errors in the ensemble members tend to compensate each other (Martre et al. 2015).

The ensemble simulations could be obtained by using individual model with multiple sets of model parameters (Tao et al., 2009a) or multiple models (Palosuo, et al., 2011; Asseng et al., 2013; Bassu et al., 2014; Martre et al., 2015; Li et al., 2015) or multiple models with multiple sets of model parameters called the super-ensemble simulation (Wallach et al., 2016). The super-ensemble simulations method accounts for uncertainties from both model structure and model parameters. In this study, the contribution of model structure was much larger than that of model parameters to model total variance. One of the major problems with the current models was that crop development rate under extreme climate events were not well formulated (Lobell et al., 2012; Zhang and Tao, 2013; Asseng et al., 2015). These cause models not to be able to simulate crop phenology well under extreme climate conditions such as extreme high or low temperature events. In addition, we found the models with similar mechanisms or structure may get similar simulations. The model errors couldn't be improved much with multiple sets of parameters in some specific year.

For example, all the models failed to simulate rice phenology accurately in 1993, 1998 and 2009 without reference to parameter values. There are two peak values for frequency distribution of temperatures in 1993, 1998 and 2009 (Fig. 9). It indicated that model performance was limited under exceptional temperature.

In fact, the model errors were intrinsically determined by the temperature response functions in the models. The development rate in most models increases when the observed temperature is lower than the optimal temperature and it declines when the observed temperature is larger than the optimal temperature. This response of development rate to temperature is supported by many previous studies (Parent et al., 2010)). However the temperature response function in SIMRIW is quite different. It has constant development rates when observed temperature is larger than 20 °C and an abrupt decline of development rate when observed temperature is larger than 35 °C. It is difficult to conclude which kind of temperature response function is true. Therefore, the uncertainty of model structure should be reduced by elaborating the temperature response function based on environment-controlled experimental data (Asseng et al., 2015).

The error of model parameters is another source of model uncertainty. Martre et al. (2015) indicated that several individual models had small errors for end-season variables (e.g. grain yield) and large errors for in-season variables (e.g. leaf area index). In some cases, crop models may get the right answer for the wrong reasons (Martre et al, 2015). It is mainly because different variables are controlled by different parameters (Wallach, 2011). Therefore, it is important to calibrate different parameters of crop model using multiple observations. For example, cardinal temperatures are considered some important parameters for crop phenology simulations. Sánchez et al (2014) suggested that cardinal temperatures are various in different crop phenology simulations for different cultivars and regions. In order to improve the performances of crop models, it is necessary to calibrate cardinal temperatures in models in advance.

Besides the limitation caused by climate condition, the number of observations used in calibration will influence the result. The contribution provided by model parameters will be changed by the different input data. Only northeastern China and southwestern China were considered in this study. In other regions the result may be different. Also, parameter correlation was not considered in our study, which will influence the uncertainty distribution.

5. Conclusions

Uncertainties associated with the five rice phenological models/modules in simulating and predicting rice phenology in two major rice production regions of China were investigated. In conclusion,

(1) All models with one set of optimal parameters had a general good performance in simulating rice heading date. In northeastern China, The RMSEs of the five models ranged from 6.09 to 6.70 days. For maturity date, the performance of each model was various. Beta model got the smallest RMSE of 4.33 days, among the five models. In southwestern China, the RMSEs of the five models ranged from 7.08 to 8.60 days for heading date. The RMSEs of the five models ranged from 4.89 to 5.42 days for maturity date.

(2) Simulations of heading and maturity date captured observations better when the multiple sets of perturbed parameters were used. However, some models can't capture observation well in some specific years without reference to parameter values, which indicated that model structure limit model performance in some cases.

(3) The models adopting temperature accumulation function (i.e., CERES-Rice and ORYZA2000) had better performance in zone II than in zone I. While the models adopting exponential function (i.e., Beta model and RCM model) had better performance in zone I than in zone II.

(4) Uncertainty from model structure was generally larger than that from model parameters.

(5) In zone I, the contribution of model structure and model parameter to model total variance was about 55.90% and 44.10%, respectively, in simulating heading date; the contribution of model structure and model parameter to model total variance was about 75.43% and 24.57%, respectively, in simulating maturity date. In zone II, the contribution of model structure and model parameter to model total variance was about 79.97% and 27.03%, respectively, in simulating heading date; the contribution of model structure and model parameter to model total variance was about 92.15% and 7.85%, respectively, in simulating maturity date.

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Figure caption:

Fig.1. Locations of the agro-meteorological experiment stations and the study area in this study.

Fig.2. Frequency distribution of temperatures during vegetative growing period (a) and reproductive growing period (b) in the zone I.

Fig 3. Relationship between rice development rate and temperature in the five models with one set of optimal parameters in zone I. (a) heading date simulated by each of the five models with its respective one set of optimal parameters; (b) maturity date simulated by each of the five models with its respective one set of optimal parameters.

Fig.4. Simulated rice heading dates and maturity dates by the five models with their respective one set of parameters in zone I.

Fig.5. Relationship between rice development rate and temperature for the five models with 50 sets of parameters in zone I. (a) heading date simulated by the five models with their respective 50 sets of parameters; (b) maturity simulated by the five models with their respective 50 sets of parameters.

Fig.6. Simulated rice heading dates and maturity dates by the (a) CERES-Rice, (b) ORYZA2000, (c) RCM, (d) Beta Model, (e) SIMRIW with 50 sets of parameters in zone I.

Fig.7. Simulated rice heading dates and maturity dates by the five models with their respective 50 sets of perturbed parameters in zone I.

Fig.8. Share of the model total variance from model structure and model parameters in simulating rice heading date (a) and maturity date (b) in zone I.

Fig.9. Frequency distribution of temperatures in 1993, 1998, and 2009 during rice growing period in zone I.

Figr-1

Fig.1. Locations of the agro-meteorological experiment stations and the study area in this study.

Figr-2

Fig.2. Frequency distribution of temperatures during vegetative growing period (a) and reproductive growing period (b) in the zone I.

Figr-3

Fig 3. Relationship between rice development rate and temperature in the five models with one set of optimal parameters in zone I. (a) heading date simulated by each of the five models with its respective one set of optimal parameters; (b) maturity date simulated by each of the five models with its respective one set of optimal parameters.

Figr-4

Fig.4. Simulated rice heading dates and maturity dates by the five models with their respective one set of parameters in zone I.

Figr-5

Fig.5. Relationship between rice development rate and temperature for the five models with 50 sets of parameters in zone I. (a) heading date simulated by the five models with their respective 50 sets of parameters; (b) maturity simulated by the five models with their respective 50 sets of parameters.

Fig-6

Fig.6. Simulated rice heading dates and maturity dates by the (a) CERES-Rice, (b) ORYZA2000, (c) RCM, (d) Beta Model, (e) SIMRIW with 50 sets of parameters in zone I.

Figr-7

Fig.7. Simulated rice heading dates and maturity dates by the five models with their respective 50 sets of perturbed parameters in zone I.

Figr-8

Fig.8. Share of the model total variance from model structure and model parameters in simulating rice heading date (a) and maturity date (b) in zone I.

Figr-9

Fig.9. Frequency distribution of temperatures in 1993, 1998, and 2009 during rice growing period in zone I.

Table 1 Statistic on the simulations using the five models with their respective one set of optimal parameters and 50 sets of perturbed parameters

Model	stage	parameters	Description	Zone I		Zone II	
				optimal value	repeturion range	optimal value	repeturion range
CERES-Rice		P1	the threshold of DTT for VGP	776.00	737.20 - 814.80	1060.00	1007.00 - 1113.00
	VGP	DL _c	critical day length	15.11	14.355 - 15.866	15.11	14.355- 15.866
		P2R	photoperiod sensitivity parameter	12.81	12.17 - 13.451	12.81	12.17 - 13.451
	RGP	P5	the threshold of DTT for RGP	510.00	484.50 - 535.50	550.00	522.50 - 577.50
ORYZA2000		DVRI	the threshold of DTU accumulation for VGP	858.00	815.1 - 900.9	1200.00	1140.00 - 1240.00
	VGP	PPSE	photoperiod sensitivity parameter	0.05	0.0475 - 0.0525	0.08	0.076 - 0.084
		DL _c	critical day length	12.50	11.875 - 13.125	12.00	11.40 - 12.40
	RGP	DVRR	the threshold of DTU accumulation for RGP	535.00	508.25 - 561.75	570.00	541.50 - 598.50
RCM		k	empirical constants	12.60	12.30 - 13.00	12.00	11.40 - 12.60
		P	empirical constants	-4.136	-4.2028 - 4.0692	-4.24	-4.312 - 4.178
	VGP	Q	empirical constants	0.406	0.3907 - 0.4163	0.35	0.3325 - 0.3675
		G	empirical constants	0.216	0.2052 - 0.2268	0.20	0.19 - 0.21
		DL _c	critical day length	-0.022	-0.0231 - 0.0209	-0.02	-0.021 - 0.019
		k	empirical constants	-3.65	-3.7325 - 3.5675	-3.365	-3.5333 - 3.2968
	RGP	P	empirical constants	0.35	0.3325 - 0.3675	0.45	0.4275 - 0.4725
		Q	empirical constants	-6.55	-6.57 - 6.53	-7.91	-7.93 - 7.89
Beta Model		μ	empirical constants	0.50	0.475 - 0.525	0.95	0.93-0.98
		α	empirical constants	0.369	0.3505 - 0.3875	0.37	0.3515- 0.3885
	VGP	β	empirical constants	-5.743	-5.78 - 5.71	-4.80	-4.82--4.78
		δ	empirical constants	0.20	0.19 - 0.21	0.20	0.19-0.21
		ε	empirical constants	0.50	0.475 - 0.525	0.30	0.285- 0.315

SIMRIW		μ	empirical constants	0.90	0.88 - 0.92	0.70	0.665- 0.735
	RGP	α	empirical constants	20.55	19.5-21.5	22.15	21.043- 23.258
		β	empirical constants	57.01	55.00 - 60.00	60.03	56.529- 63.532
		DL _c	critical day length	0.20	0.18 - 0.23	0.28	0.266- 0.294
		T _h	the temperature at which DVR is half the maximum rate at the optimum temperature	13.96	13.5 - 14.5	20.31	19.294- 21.326
	VGP	G _v	the minimum number of days required for heading	0.94	0.893 - 0.987	0.58	0.551- 0.609
		A	empirical constants	0.47	0.4465 - 0.4935	0.11	0.1045- 0.1155
		B	empirical constants	8.00	7.60 - 8.40	10.00	9.5-10.5
		G _r	the minimum number of days for grain-filling period	44.00	41.80 - 46.20	25.00	23.75- 26.25
	RGP	K _r	empirical constants	776.00	737.20 - 814.80	1060.00	1007-1113
		T _{cr:}	empirical constants	15.11	14.355 - 15.866	15.11	14.355- 15.866

Table2 Statistic on the simulations using the five models with their respective one set
of optimal parameters and 50 sets of perturbed parameters

		Zone I						Zone II					
		Heading date			Maturity date			Heading date			Maturity date		
		RMSE (days)	r	Bias (days)	RMSE (days)	R	Bias (days)	RMSE (days)	r	Bias (days)	RMSE (days)	r	
One Model with one set of parameters	CERES-Rice	6.70	0.27	0.02	8.71	0.53	-1.28	7.08	0.82	-0.20	4.97	0.94	
	ORYZA2000	6.62	0.30	-0.77	9.12	0.54	-2.50	7.78	0.81	2.81	5.42	0.94	
	RCM	6.09	0.30	-1.89	4.81	0.66	-1.31	8.60	0.80	-0.93	4.56	0.94	
	Beta Model	6.45	0.29	-2.59	4.33	0.66	-0.46	7.62	0.82	-0.81	5.17	0.93	
	SIMRIW	6.36	0.27	-0.76	4.44	0.67	-1.26	7.90	0.84	4.06	4.89	0.94	
One Model with 50 sets of parameters	CERES-Rice	6.70	0.27	-0.23	8.89	0.52	-0.86	7.15	0.81	-0.61	4.90	0.94	
	ORYZA2000	6.73	0.30	-1.46	6.71	0.60	0.31	7.64	0.81	2.23	4.70	0.94	
	RCM	6.63	0.29	-3.18	5.28	0.66	2.41	8.58	0.80	-0.42	4.58	0.94	
	Beta Model	6.49	0.30	-2.78	4.23	0.66	-0.40	8.23	0.82	-3.33	5.18	0.93	
	SIMRIW	6.26	0.28	-0.12	4.46	0.66	-1.08	8.42	0.84	5.00	4.83	0.94	
Five Models with one set of parameters		5.86	0.34	-0.83	4.81	0.65	-1.36	6.74	0.86	1.24	4.67	0.94	
Five Model with 50 sets of parameters		6.36	0.28	-1.23	5.13	0.63	0.47	7.40	0.81	0.37	4.66	0.94	