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Integration of Calibration and Forcing Methods for Predicting Timely Crop States by Using AquaCrop-OS Model

Tianxiang Zhang, Jinya Su, Cunjia Liu, Wen-Hua Chen, IEEE, Fellow
Department of Aeronautical and Automotive Engineering, Loughborough University
Loughborough, LE11 3TU, U.K

***Abstract*— This paper presents a framework for predicting canopy states in real time by adopting a recent MATLAB based crop model: AquaCrop-OS. The historical observations are firstly used to estimate the crop sensitive parameters in Bayesian approach. Secondly, the model states will be replaced by updating remotely sensed observations in a sequential way. The final predicted states will be in comparison with the groundtruth and the RMSE of these two are 39.4155 g/m^2 (calibration method) and 19.3679 g/m^2 (calibration with forcing method) concluding that the system is capable of predicting the crop status timely and improve the performance of calibration strategy.**

Keywords-data assimilation; Bayesian calibration; sequential forcing method; crop model; remote sensing; states prediction

I. INTRODUCTION

Timely and accurate estimation of crop status before harvest allow framers to make a decision on field management and irrigation plan, which is of importance for national food security assessment and maximining the economic impacts [1]. Therefore, crop model has been improved from qualitative research to quantitative research simulating the whole growth phase under various stress, like WOFOST, DASSAT, STICS and AquaCrop model [2-5]. Individual crop model performance may be affected due to the uncertainties of soil properties, canopy states and meteorological data resulting in a large error in crop states prediction when localized in one certain area. These uncertainties of crop growth model can be reduced by providing more information to improve model parametrization and calibration and increase the final data assimilation accuracy.

There are three approaches to employ remotely sensed data into crop model: parameter calibration, forcing method and update method. Jin et al. adopted particle swarm optimization (PSO) method to calibrate AquaCrop model by using historical remote sensing data making a prediction of biomass and final yield before harvest [6]. Moreover, Tripathy et al. directly replaced model predict leaf area index (LAI) by index-based LAI to improve the prediction performance [7]. The rapid development of remote sensing platforms provides high property data with high spectral and spatial resolutions accurately estimating the crop states than ever. The integration of crop model and remotely sensed data has been an effective tool to not only calibrate the crop model but also make a prediction in time.

The new water driven crop model, AquaCrop, with characters of simplicity, robustness, accurateness, was proposed in 2009 by Steduto indicating better results in predicting crop growth status. Compared with other crop models, the AquaCrop simulation model can model the dynamic change of crop growth status in response to water [8]. According to the principle of AquaCrop model, Foster et al. developed it into an open-access software AquaCrop-OS programmed by MATLAB enabling the code to be linked quickly with other disciplinary models to support yield estimation, water resource management and intelligent irrigation program in 2016 [9].

From previous literature, most of the researchers focus on adopting the data assimilation method individually, however, each method has their own limitation on crop states prediction. Calibration strategy always relies on the historical data and cannot make real-time prediction. Forcing method will involve in new observation error. In addition, update method is also flawed as it requires expensive calculation and new uncertainties. In our paper, a real time crop states prediction system is presented to combine calibration strategy and forcing method to reduce the parameters uncertainties and improve a timely prediction.

The summary of the contribution in this paper is organized as follows:

1. Rather than traditional optimization-based calibration, a Bayesian-based parameter estimation method is pointed.
2. It is the first time to program the AquaCrop-OS model to realize a sequential update function.
3. The integration of calibration method and forcing method is able to predict the processed states variables in real time
4. In addition to the timely sates, weather information can also be updated timely.

II. METHODOLOGY

In this section, materials related to our research will be presented, including whole framework, model formulation, data collection, calibration strategy and forcing method strategy. Due to the character that the model can simulate most

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of the crops, like spring wheat, spring wheat, maize and corns. A specific simulation time from 05/10/2014 to 30/05/2015 on winter wheat was chosen.

A. Framework

As is shown in Fig. 1, the whole framework of real-time states variables prediction is divided into two stages: crop sensitive parameters estimation and forcing method data assimilation. The calibration process is to estimate the most sensitive parameters with the historical remote sensing data by Bayesian estimation based on Markov Chain Monte Carlo (MCMC) techniques. Additionally, the timely updated data will be assimilated into the AquaCrop-OS model by employing forcing method.

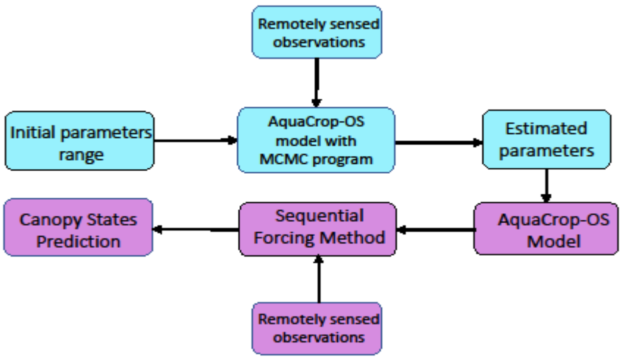

Fig. 1 The framework of real-time states prediction system

B. Model Formulation

The AquaCrop-OS model are programmed by using Markov process on the basis of AquaCrop model. A simplified formulation can be achieved according to Eq. 1 and Eq. 2.

$$X_{t+1} = f(X_t, \theta') \quad (1)$$

$$Y_{t+1} = g(X_t, \theta') + \varepsilon_t \quad (2)$$

where f represents the AquaCrop-OS function relative with all required crop parameters θ' and the states variables X. Y indicates the measurement with a proper mean and variance gaussian noise ε_t.

C. Data Preparation

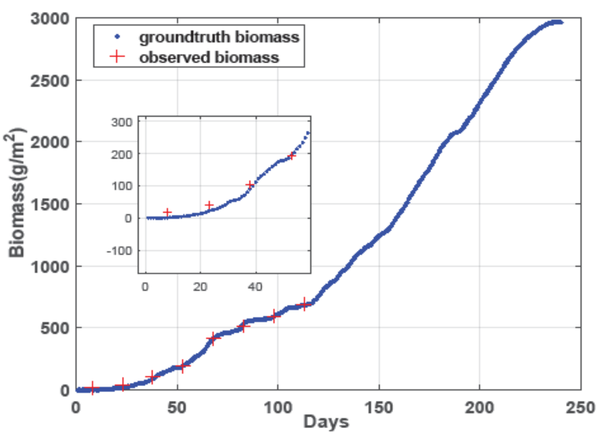

Fig. 2 Biomass groundtruth and observation data

In our study, due to the lack of real remotely sensed data, the simulated observations can be produced by groundtruth states adding a Gaussian noise. The default parameters of AquaCrop-OS model are described as the truth parameters and thus generating groundtruth states variables. Biomass and canopy cover are selected as the state variables for model calibration and sequential forcing (see Fig. 2, Fig. 3). There are eight-day observations totally, the first five-day historical observations of biomass and canopy cover are adopted for estimating the crop parameters, and the overall eight-day measurements is employed for forcing method.

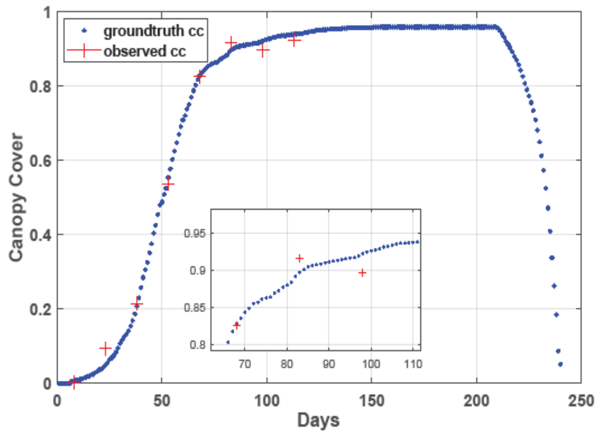

Fig. 3 Canopy cover groundtruth and observation data

D. Calibration Strategy

In our case, the sensitive parameters to be calibrated is selected as θ = [gdd, p_up3, wp, cgc, ccx, mat, eme, kcb] describing the typical characters during crop growth and treated as uniform distribution. The historical observations are selected at intervals of 15 days from day 8 to day 68 for crop model parameter calibration.

Bayesian calibration aims to derive the posterior probability distributions for parameters of interest conditional on measurements, where the uncalibrated parameter posterior distribution $p(\theta|D)$ is proportional to the prior distribution $p(\theta)$ and the measurement likelihood function $p(D|\theta)$, given by:

$$p(\theta|D) \propto p(\theta) \times p(D|\theta) \quad (4)$$

where θ means the pending parameter vectors and D represents the observed data. The likelihood function $p(D|\theta)$ evaluates each value for θ on the basis of how well the model with parameter θ is able to reproduce the data D [8].

To effectively estimate the parameters posterior distribution that direct sampling is difficult, a Markov Chain Monte Carlo (MCMC) algorithm entitled Metropolis-Hastings algorithm is employed.

E. Forcing Method

The model uncertainties have been reduced by estimating the sensitive parameters with the historical measurement. Forcing method can provide the researchers a feasible way to directly replace the crop model simulation data by timely observation data where the time step can be daily, weekly or monthly, offering the farmers a chance for real-time decision make [1]. In our case, the total of 8 observations will be conducted to do forcing method.

III. Results

In this part, the model calibration results and forcing method prediction results will be presented. The estimated parameters involving biomass and canopy cover measurements will be compared with the truth; meanwhile, the forcing strategy embedded calibration results will be in comparison with calibration strategy by using the remaining days states from the whole growth period.

A. *Parameters Estimation Results*

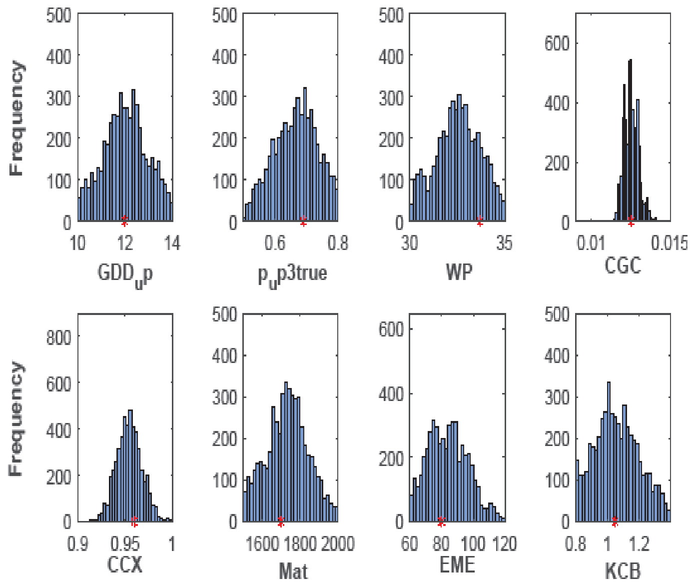

Fig. 4 Estimated parameters posterior distribution

The posterior distribution with the observations is shown in Fig. 4, where the red star represents the truth parameters. The mean value was calculated of each parameter distribution and compared with the truth parameter (see TABLE I). The error of each parameters is less than 4% with truth parameter, moreover, the overall error of eight parameters is only 2.2902% (see Eq. 3). The result is corresponding to the literature [8] decreasing the uncertainties.

TABLE I. COMPARISION BETWEEN ESTIMATED AND TRUTH PARAMETERS

Sensitive Parameters	Estimated Parameters	Truth Parameters	Error (%)
GDD_up	12.0187	12	0.1557
P_up3	0.6648	0.69	3.6494
WP	32.5386	33.7	3.4463
CGC	0.0125	0.0125	0.0220
CCX	0.9544	0.96	0.5845
MAT	1733	1700	1.9514
EME	84.0916	80	5.1145
KCB	1.0616	1.05	1.1073
Average			**2.2902**

$$\text{Error} = \frac{|\text{Estimated Parameters} - \text{Truth Parameters}|}{\text{Truth Parameters}} * 100\% \quad (3)$$

B. *Forcing Method Results*

Forcing method is able to provide a timely update strategy after directly replace the model data by observations. The prediction states of AquaCrop-OS applying forcing method are shown in Fig. 5-6. Compared with goundtruth, the Root Mean Squared Error (RMSE) of predicted biomass with the technique of parameter estimation and forcing method embedded parameter estimation are 39.4155 g/m^2 and 19.3679 g/m^2, respectively.

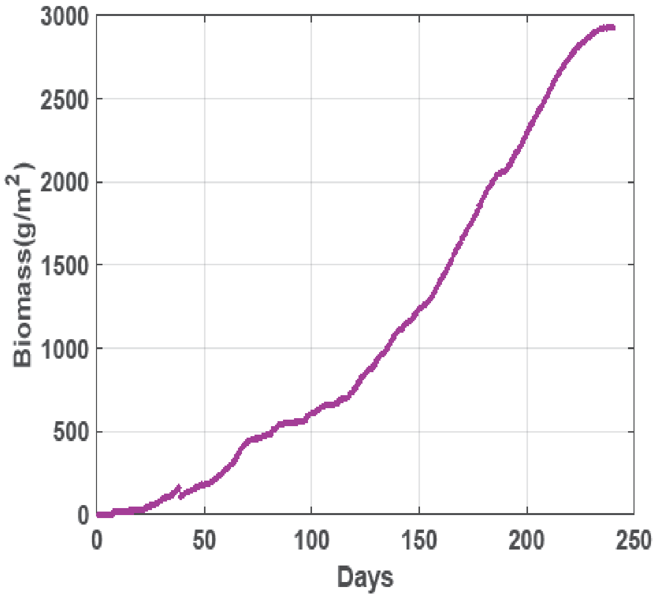

Fig. 5 Real time prediction by forcing timely biomass

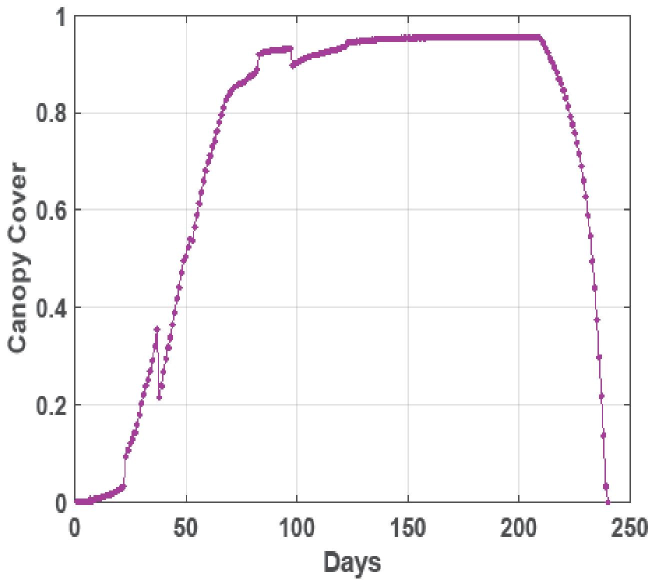

Fig. 6 Real time prediction by forcing timely canopy cover

The states prediction of various method with the observation of biomass can also be obtained from Fig. 7, which can be concluded that the real-time system prediction line is much closer to truth states. The prediction performs better especially after forcing method.

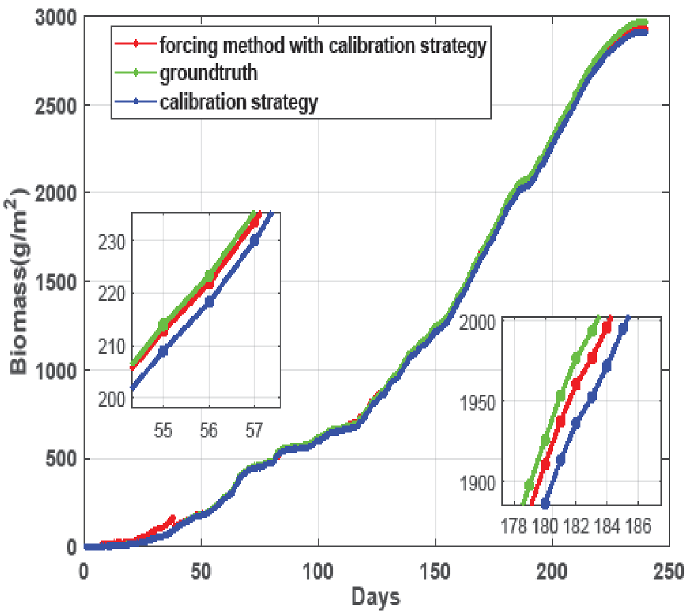

Fig. 7 Comparison of predicted biomass with different methods

IV. Conclusion

This work aims at exploiting the potentials of integrating calibration strategy and forcing strategy on crop states timely prediction with multiple observations. Results showed that the performance of our system outperforms individual calibration strategy, especially after new measurement updates. Therefore, it can be used on states variables prediction and irrigation decision-making or field management during the period of crop growth.

V. Future Works

Future work on this direction is summarized in the following aspects:

(i) To reduce the uncertainties of observations in forcing method, some sequential Monte Carlo algorithm could be applied, such as Particle Filter.

(ii) Crop parameters and crop states can be estimated at the same time during particle filter process.

(iii) Remote sensing data may also be collected from UAVs at a higher spectral resolution.

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