Inter-comparison of wheat models to identify knowledge gaps and improve process modeling

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Introduction

An intercomparison of wheat models revealed that the uncertainty in simulated yield increases with rising temperature (Asseng et al., 2013) and the mean of the multi-model ensemble (MME) simulations best matched the observations (Martre et al., 2015). These findings highlight the need for MME approach to better address yield projection uncertainty. However, the MME approach itself does not lead to improvement in process understanding. Here we extend the model intercomparison to investigate how the uncertainties in simulation results arise from process-level algorithms and parameterization in the models and to identify knowledge gaps.

Materials and Methods

We systematically compared 29 wheat models (Asseng et al., 2015) in terms of how key temperature-responsive physiological processes are simulated. We extracted the algorithms used in these models and categorized the temperature response equations into four types based on how the cardinal temperatures are defined. To demonstrate the impact of the different temperature equations on simulated phenology, total above ground biomass and grain yield, we implemented the four types of temperature responses in the APSIM and *SiriusQuality* models and tested the modified models against the Hot Serial Cereal field experiment (Wall et al., 2011).

Results and Discussion

Our analysis revealed contrasting temperature response functions used for the same physiological process among different models. These differences impacted directly on the sensitivity of simulated yield to temperature changes, particularly at high temperature range. The range of simulated yield caused by variations of temperature response functions in APSIM and *SiriusQuality* was on average 52 % and 64 % of the uncertainty of the MME, respectively. These results demonstrate that the contrasting temperature response functions implemented in the models is a major cause of the uncertainty in the simulated yield. Finally, we developed improved temperature response functions for key processes. Their implementation into APSIM and *SiriusQuality* led to improved yield simulations.

Conclusions

The contrasting temperature response functions for simulating key physiological processes in current wheat models are a major cause of the uncertainty in simulated yield. Inter-comparison of modeling approaches enabled to identify knowledge gaps and improvement in process modeling.

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