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Crop model improvement reduces the uncertainty of the response to temperature of multi-model ensembles

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A B S T R A C T

To improve climate change impact estimates and to quantify their uncertainty, multi-model ensembles (MMEs) have been suggested. Model improvements can improve the accuracy of simulations and reduce the uncertainty of climate change impact assessments. Furthermore, they can reduce the number of models needed in a MME. Herein, 15 wheat growth models of a larger MME were improved through

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re-parameterization and/or incorporating or modifying heat stress effects on phenology, leaf growth and senescence, biomass growth, and grain number and size using detailed field experimental data from the USDA Hot Serial Cereal experiment (calibration data set). Simulation results from before and after model improvement were then evaluated with independent field experiments from a CIMMYT worldwide field trial network (evaluation data set). Model improvements decreased the variation (10th to 90th model ensemble percentile range) of grain yields simulated by the MME on average by 39% in the calibration data set and by 26% in the independent evaluation data set for crops grown in mean seasonal temperatures >24 °C. MME mean squared error in simulating grain yield decreased by 37%. A reduction in MME uncertainty range by 27% increased MME prediction skills by 47%. Results suggest that the mean level of variation observed in field experiments and used as a benchmark can be reached with half the number of models in the MME. Improving crop models is therefore important to increase the certainty of model-based impact assessments and allow more practical, i.e. smaller MMEs to be used effectively.

1. Introduction

Wheat is the most widely grown crop in the world and provides more than 20% of the daily protein and food calories for the world population (Shiferaw et al., 2013). With a predicted world population of 9 billion in 2050, the demand for food including wheat is expected to increase by then (Alexandratos and Bruinsma, 2012). Climate trends are significantly affecting agricultural production systems, including wheat, in several regions of the world, thereby posing risks to global food supply and security (Sundström et al., 2014). Therefore, quantifying the potential impact of climate variability on crops has become a priority in order to develop effective adaptation and mitigation strategies (Burton and Lim, 2005; Denton et al., 2014).

Process-based crop simulation models are useful tools to assess the impact of climate as they consider the interaction between climate variables and crop management and their effects on crop productivity. Their use in climate impact studies and for analyzing and developing adaptation and mitigation strategies has increased during the recent years (Byjesh et al., 2010; Donatelli et al., 2012; Moradi et al., 2013; Rosenzweig et al., 2014). Nevertheless, most of the current crop models lack explicit definitions of relevant physiological thresholds and crop responses to extreme weather events, particularly for temperatures exceeding these thresholds (Rötter et al., 2011). These omissions might be one of the reason for the considerable differences in estimates of grain yield observed among models especially for high temperatures, and between models and field observations (Palosuo et al., 2011). In addition, since a clear methodology is lacking, most climate change impact assessments for agriculture have not addressed crop model uncertainties (Müller, 2011), which have become a major concern recently in climate impact assessments (Lobell et al., 2006; Ruane et al., 2013; Zhang et al., 2015).

White et al. (2011) reported that over 40 wheat crop models are in use worldwide. They differ in the processes they include, or in the modelling approaches used to simulate physiological processes. A recent work carried out by the Wheat Team of the Agricultural Model Inter-comparison and Improvement Project (AgMIP) (Rosenzweig et al., 2013) compared 27 wheat crop models and showed that a greater portion of the uncertainty in climate change impact projections was due to variations among crop models than to variations among climate models, and that uncertainties in simulated yield increased dramatically under high temperature conditions (Asseng et al., 2013). Following the example of the climate modelling community, to increase reliability of impact estimates and to give better estimates of uncertainty, use of crop multi-model ensembles (MME) has been suggested (Asseng et al., 2015; Bassu et al., 2014; Li et al., 2015; Pirttioja et al., 2015). Model improvements have been suggested for improving the accuracy of simulations and reducing the uncertainty of climate impact assessments (Asseng et al., 2013; Challinor et al., 2014; Rötter et al., 2011). Martre et al. (2015) argued that one of the consequences of model improvements will be the reduction of the number of models required for an acceptable level of simulation uncertainty. Furthermore, the improvement of the models in an ensemble using good quality field-based experimental data could substantially widen the range of research questions to be addressed and increase the confidence in simulation results of applications under changed climatic or management conditions (Martre et al., 2015).

Herein, we investigated the effects of model improvements in 15 wheat crop models with regards to heat stress and its impact on model performances, uncertainty, and the number of crop models required in multi-model ensembles used for impact studies.

2. Materials and methods

2.1. Experimental data

Detailed quality-assessed data from the USDA ‘Hot Serial Cereal’ (HSC) experiment (Grant et al., 2011; Kimball et al., 2015; Ottman et al., 2012; Wall et al., 2011) and from the ‘International Heat Stress Genotype Experiment’ (IHSGE) coordinated by CIMMYT (Reynolds et al., 1994b) were used. Both experiments were well watered and fertilized to avoid drought and nutritional stress to assure that temperature would be the main environmental variable. Daily global solar radiation, maximum and minimum air temperature, average wind speed, dew point temperature and precipitation were recorded at weather stations near the experimental plots. The mean daily average air temperature for the growing season (sowing to physiological maturity) was calculated from minimum and maximum daily air temperatures as described in Asseng et al. (2015) and reported in Supplementary Information S2. In both experiments phenological development measurements included: emergence date (Zadock scale 10), anthesis date (Zadock scale 65), and maturity date (Zadock scale 89). From these measurements the number of days from sowing to anthesis (days), from anthesis to maturity (days), and from sowing to maturity (days) were calculated. In both experiments, the plots were kept weed-free, and plant protection methods were used as necessary to minimize damage from pest and diseases. The two data sets are further described in Asseng et al. (2015). Following is a brief description with focus on the measurement data that were available for this study.

The HSC experiment was conducted at Maricopa, AZ, USA (33.07°N, 111.97° W, 361 m a.s.l.): The spring wheat cultivar ‘Yecora RojO’ was sown about every six weeks for two years, and infrared heaters were deployed on six of the sowing dates in a T-FACE (temperature free-air controlled enhancement) system which warmed the canopies of the heated plots on average by 1.3 °C and 2.7 °C