Rising temperatures reduce global wheat production

S. Asseng et al.†

Crop models are essential tools for assessing the threat of climate change to local and global food production. Present models used to predict wheat grain yield are highly uncertain when simulating how crops respond to temperature. Here we systematically tested 30 different wheat crop models of the Agricultural Model Intercomparison and Improvement Project against field experiments in which growing season mean temperatures ranged from 15°C to 32°C, including experiments with artificial heating. Many models simulated yields well, but were less accurate at higher temperatures. The model ensemble median was consistently more accurate in simulating the crop temperature response than any single model, regardless of the input information used. Extrapolating the model ensemble temperature response indicates that warming is already slowing yield gains at a majority of wheat-growing locations. Global wheat production is estimated to fall by 6% for each °C of further temperature increase and become more variable over space and time.

Understanding how different climate factors interact and impact food production is essential when reaching decisions on how to adapt to the effects of climate change. To implement such strategies, the contribution of various climate variables on crop yields need to be separated and quantified. For instance, a change in temperature will require a different adaptation strategy than a change in rainfall. Temperature changes alone are reported to have potentially large negative impacts on crop production, and hotspots—locations where plants suffer from high temperature stress—have been identified across the globe. Crop simulation models are useful tools in climate impact studies as they deal with multiple climate seasons, including experiments with artificial heating. Many models simulated yields well, but were less accurate at higher temperatures. The model ensemble median was consistently more accurate in simulating the crop temperature response than any single model, regardless of the input information used. Extrapolating the model ensemble temperature response indicates that warming is already slowing yield gains at a majority of wheat-growing locations. Global wheat production is estimated to fall by 6% for each °C of further temperature increase and become more variable over space and time.

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The differences between simulated and observed yields revealed considerable uncertainty, as reported in a previous systematic sensitivity analysis with a large crop model ensemble. Uncertainty increased, particularly at higher temperatures, with models deviating from the observed data at $T_{\text{max}} > 22 \, ^\circ\text{C}$. However, many of the models simulated the yield decline due to increasing temperatures within the measurement errors ($\pm 1$ s.d.). Notably the median of the ensemble of 30 models consistently had the best or near-best skill in reproducing the observed temperature impacts on grain yield, as shown for other crop model ensembles that simulated present growing conditions. When considering the subset of treatments in the HSC experiment that were heated artificially in the field with infrared heaters, the simulated relative impact of increased temperature was mostly within the observed relative impact range, and was largest when reference or background temperatures were the highest (Supplementary Fig. 4). In general, the uncertainty in both observed and simulated impacts was relatively large for the artificially heated crops (Supplementary Fig. 4).

Information on cultivars and crop management needed for regional or global modelling studies is sparse. Lack of such information can affect the outcomes of an impact assessment owing to large model input uncertainties. Here, further information on cultivar parameters and phenology improved grain yield simulations for a few individual models (Supplementary Table 4), consistent with previous findings, but had little or even a negative impact on the performance of many other models—and, therefore, on the multi-model ensemble median (Supplementary Fig. 10). Therefore, when using a single model to assess climate change impact, the simulated impacts varied widely depending on the individual model and available information, but the level of information hardly affected the accuracy of the ensemble median impact simulations.

The simulated phenology in crop models can have a large impact on the simulations of other crop processes. When simulating grain yields with a 'fixed phenology', modellers were asked to fix their simulated anthesis and maturity dates as close as possible to the observed dates (that is, root mean square relative error (RMSRE) for anthesis and maturity dates were close to zero (Supplementary Table 4)) to override any input errors from phenology simulations. Fixing phenology when simulating grain yields had a surprisingly minor effect, and subsequent ensemble yields hardly changed (Supplementary Fig. 10). Furthermore, small errors in simulated phenology did not necessarily translate into errors in yield, particularly if there was compensation between the modelling of pre- and post-anthesis processes. This trade-off between pre-anthesis growth and post-anthesis stress exposure is well-documented in late-in-season drought environments and can be managed by altering sowing dates, cultivar choice and fertilizer inputs. In well-fertilized, irrigated systems without initial water stress, a later-flowering crop will accumulate more biomass and a potentially higher yield, but if it is then exposed to more heat late in the season, grain filling and final grain yield will be reduced. Many models simulated this interaction correctly, compensating for other errors which may disguise erroneous model structures or parameters.

We have shown with the large range of observed data that the simulated wheat crop model ensemble median consistently has better skill in reproducing the observed temperature response than single models and that the level of information on cultivars had little effect on the ensemble median accuracy. Therefore, this 30-model ensemble provides the most accurate estimate of wheat yield response to increased temperature (Fig. 2). Although improvements in technology and management have led to increasing wheat yields around the world, wheat model simulations over the main global wheat-producing regions can isolate the climate signal by holding inputs and management constant with the exception of climate information. Simulated yields declined between 1981 and 2010 (Fig. 2a) at 20 of the 30 representative global locations (Supplementary Figs 11–13) owing to positive temperature trends over the same period (Supplementary Fig. 1). The simulated median temperature impact on yield decline varied widely across 30 global locations and the 30-year average yields decreased by between 1% and 28% across sites with an increase of 2 $^\circ\text{C}$ in temperature and between 6% and 55% across sites with an increase of 4 $^\circ\text{C}$ (Fig. 2b,c).

For locations at low latitudes the increase in simulated yield variability with higher temperature was more marked than at high latitudes, because the relative yield decline was greater owing to the higher reference temperatures (Fig. 2c). However, yield variability expressed in absolute terms hardly changed (Supplementary Fig. 14). Similarly, the year-to-year variability increased at some locations with temperature increases because of greater relative yield reductions in warmer years and lesser reductions in cooler years (Fig. 3a). The increase in year-to-year yield variability is
critical economically as it could decrease some regional—and hence global—stability in wheat grain supply\(^1\), amplifying market and price fluctuations\(^1\).

About 70% of present global wheat production comes from irrigated or high-rainfall regions\(^2\). The global temperature impact simulations were carried out for region-specific cultivars, including spring and winter wheat cultivars (Supplementary Table 3), at key locations in irrigated or high-rainfall regions. All locations had a model ensemble median yield loss on average over 30 years with increasing temperatures (Fig. 2), mainly as a result of a reduced growing period with fewer grains per unit land area (Fig. 3b), also supported by field experiments\(^1\). Mediterranean-type and arid environments have been studied with single models. Under rain-fed and water- and nitrogen-limited conditions, it was found that seasonal temperature increases of up to 2 °C increased yields by avoiding water and heat stress at the end of the season\(^2\). However, other experimental evidence suggests that increased temperature has negative impacts regardless of water\(^2\) (Supplementary Figs 15 and 16) and N supply\(^2\) (Supplementary Fig. 17). Therefore, the simulated temperature impacts are possibly applicable to most cropping systems beyond those that are irrigated or that receive high rainfall. To attempt a global temperature impact estimate, we extrapolated the simulated temperature impacts of the 30 chosen experimental locations to all regional wheat production using country statistics (http://www.fao.org) and disaggregated global mean surface temperature increases to regional surface temperature changes\(^2\) (see Supplementary Methods and Table 3). For each °C increase in global mean temperature, there is a reduction in global wheat grain production of about 6%, with a 50% probability of between −4.2% and −8.2% loss, based on the multi-model ensemble. Considering present global production of 701 Mt of wheat in 2012 (http://www.fao.org) and impacts of temperature only, and assuming no change in production areas or management\(^2\), 6% means a possible reduction of 42 Mt per °C of temperature increase. To put
this in perspective, the amount is equal to a quarter of global wheat trade, which reached 147 Mt in 2013 (http://apps.fas.usda.gov). Contrary to some single-model assessments on temperature impacts\textsuperscript{21,22} and a recent multi-model global gridded impact assessment which considered several climate factors together\textsuperscript{4}, in response to global temperature increases grain yield declines are predicted for most regions in the world. By extensively ground-truthing models with field measurements and significantly reducing model uncertainty by using model ensemble medians, we demonstrate that wheat yield declines in response to temperature impacts only are likely to be larger than previously thought\textsuperscript{2} and should be expected earlier, starting even with small increases in temperature (Fig. 2).

This study, based on a multi-model ensemble and linked to field data, provides a comprehensive global temperature impact assessment for wheat production. There are several adaptation options to counter the adverse effects of climate change on global wheat production—and for some regions this will be critical. Ensemble crop modelling could be an important exploratory tool in breeding for identified genetic targets\textsuperscript{2} to extend grain filling, delay maturity and improve heat tolerance in wheat cultivars and other cereals.

Methods
We systematically tested multiple models against field and artificial heating experiments, focusing only on temperature responses. Thirty wheat crop simulation models, 29 deterministic process-based simulation models and one statistical model (Supplementary Tables 1 and 2), were compared with two previously unpublished data sets from quality-assessed field experiments from sentinel sites (see Supplementary Methods) within the Agricultural Model Intercomparison and Improvement Project\textsuperscript{23} (AgMIP; http://www.agmip.org). The first data set was from a ‘Hot Serial Cereal’ (HSC) experiment with the wheat cultivar Yecora Rojo sown on different dates with artificial heating treatments under well-irrigated and fertilized field conditions\textsuperscript{11}. The second data set was from International Maize and Wheat Improvement Center (CIMMYT) experiments testing several cultivars in seven temperature regimes with full irrigation and optimal fertilization and with different sowing date treatments\textsuperscript{11}. Using the 30 models, the temperature responses were then extrapolated in a simulation experiment with 30 years of historical climate data from 30 main wheat-producing locations (see Supplementary Methods). Model simulations were executed by individual modelling groups.

Received 4 July 2014; accepted 18 November 2014; published online 22 December 2014

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The authors declare no competing financial interests.

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Competing financial interests

The authors declare no competing financial interests.

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