Rising temperatures reduce global wheat production

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Crop models are essential tools for assessing the threat of climate change to local and global food production[1]. Present models used to predict wheat grain yield are highly uncertain when simulating how crops respond to temperature[2]. 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[3] 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[4]. Temperature changes alone are reported to have potentially large negative impacts on crop production[5], and hotspots—locations where plants suffer from high temperature stress—have been identified across the globe[6,7]. Crop simulation models are useful tools in climate impact studies as they deal with multiple climate factors and how they interact with various crop growth and yield formation processes that are sensitive to climate. These models have been applied in many studies, including the assessment of temperature impacts on crop production[1,8]. However, none of the crop models have been tested systematically against experiments at different temperatures in field conditions. Although many glasshouse and controlled-environment temperature experiments have been described, they are often not suitable for model testing as the heating of root systems in pots[9] and effects on micro-climate differ greatly from field conditions[10]. Detailed information on field experiments with a wide range of sowing dates and infrared heating recently became available for wheat[11,12]. Such experiments are well suited for testing the ability of crop models to quantify temperature responses under field conditions. Testing the temperature responses of crop models is particularly important for assessing the impact of climate change on wheat production, because the largest uncertainty in simulated impacts on yield arises from increasing temperatures[2].

In a 'Hot Serial Cereal' (HSC) well-irrigated and fertilized experiment with a single cultivar, the observed days after sowing (DAS) to maturity declined from 156 to 61 days when growing season mean temperatures (T_{mean}) increased from 15 °C to 26 °C (Fig. 1a,b). The performances of individual models are illustrated

in Supplementary Fig. 3. Note that simulations were carried out in a 'blind' test (modellers had access to phenology and yield data of one of the treatments only (normal temperature); see Supplementary Methods). Higher temperatures thus decreased the number of days during which plants could intercept light for photosynthesis, with consequent reductions in biomass (Supplementary Fig. 5) and grain yields (Fig. 1). When T_{mean} was >28 °C and when there were extremely high temperatures early in the growing season with many days of maximum temperature (T_{max}) > 34 °C, a critical maximum temperature for wheat[13], crops did not reach anthesis or grain set, so it was not possible to record anthesis or maturity dates and the yields were zero (Fig. 1a–c and Supplementary Fig. 6a–c). Observed grain yields declined from about 8 t ha^{-1} when T_{mean} was 15 °C to zero when T_{mean} was >28 °C (Fig. 1c).

Many wheat models simulated the observed anthesis and maturity dates and grain yields when T_{mean} was between 15 °C and 20 °C. However, when T_{mean} reached about 22 °C, observed grain yield measurements were more variable—that is, they had larger standard deviations (s.d.), and models started to deviate from observations (Fig. 1a–c). In some cases, observed grain yields differed by up to 0.7 t ha^{-1} (17% of average yield) with the same T_{mean}. For example, at T_{mean} of 22.3 °C, some growing seasons had early warmer temperatures that advanced anthesis dates, but cooler temperatures during grain filling that delayed maturity dates, resulting in higher yields. Other seasons had early cooler temperatures during the season that delayed anthesis dates, but warmer temperatures during grain filling that advanced maturity dates, resulting in lower yields. These warmer-to-cooler and cooler-to-warmer thermal variations created disparity even though the overall T_{mean} was the same (Supplementary Fig. 7). As these opposing thermal regimes affect development, gas exchange and water relations of wheat[12], it is important to consider in-season dynamics when determining grain yield. Many models simulated the dynamic effects on growth (Supplementary Fig. 5a) and yield well (Fig. 1). However, unexplained differences between simulations and some observed yields also exist at around 15 °C, where some of the experimental errors are also large (Fig. 1c). At a seasonal mean temperature of 29 °C the observed yield was zero and a few models that included heat stress routines affecting canopy senescence, but not necessarily, were able to simulate close-to-zero above-ground biomass and a zero or close-to-zero yield (Supplementary Figs 3c and 5). At a seasonal mean temperature of 32 °C, about a quarter of all models and the multi-model ensemble median represented the observed zero yields well (Fig. 1c and Supplementary Fig. 3c), as a result of simulated premature crop death, which was consistent with the observations (Supplementary Fig. 5).

A second experimental data set was analysed, focusing on two different cultivars grown at well-irrigated and fertilized International Maize and Wheat Improvement Center (CIMMYT) global sites. The number of days to anthesis and to maturity declined with increasing temperatures, accompanied by yield loss. Model

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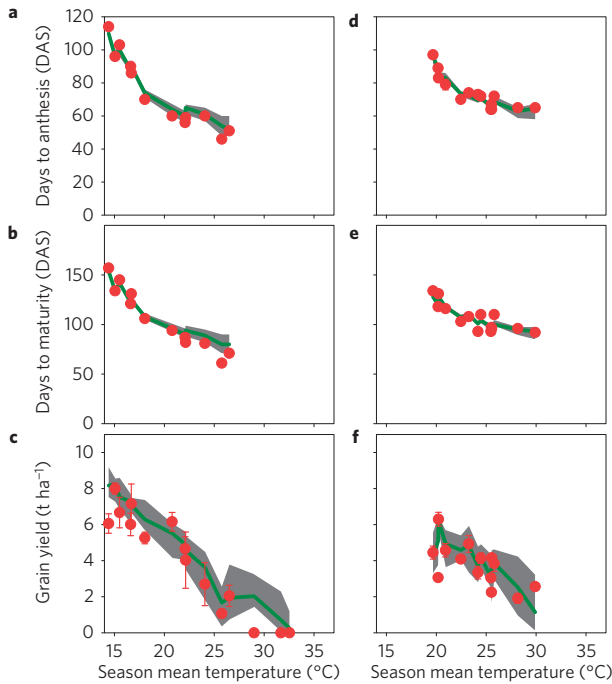
Figure 1 | Observations and multi-model simulations of wheat phenology and grain yields at different mean seasonal temperatures. a–f, Observed values ± 1 standard deviation (s.d.) are shown by red symbols. Multi-model ensemble medians (green lines) and intervals between the 25th and 75th percentiles (shaded grey) based on 30 simulation models are shown. **a–c,** 'Hot Serial Cereal' experiment on *Triticum aestivum* L. cultivar Yecora Rojo with time-of-sowing and infrared heat treatments. DAS, days-after-sowing. **d–f,** CIMMYT multi-environment temperature experiments on *T. aestivum* L. cultivar Bacanora with time-of-sowing treatments. Note, no anthesis and maturity date measurements were available >28 °C in **a** and **b** owing to premature death of crops. For details of field experiments and calibration steps, see Supplementary Methods. Error bars are not shown when smaller than the symbol.

simulations showed the same temperature responses (Fig. 1d–f and Supplementary Fig. 9). However, unlike the HSC experiment, crops did not fail with $T_{mean} > 28$ °C and still yielded about 2 t ha^{-1} of grain. This was despite similar T_{max} in both experiments during the time after sowing and before the HSC crop died (that is, about 28 DAS; Supplementary Fig. 8). The cultivars Bacanora (Fig. 1d–f) and Nesser (Supplementary Fig. 9) used in the CIMMYT experiments in various locations might be more heat tolerant than the cultivar Yecora Rojo[11] used in the HSC experiment (Fig. 1a–c). It is known that cultivars have different heat tolerance mechanisms associated with canopy temperature depression via stomata opening and transpirational cooling[14].

The differences between simulated and observed yields revealed considerable uncertainty, as reported in a previous systematic sensitivity analysis with a large crop model ensemble[2]. Uncertainty increased, particularly at higher temperatures, with models deviating from the observed data at $T_{mean} > 22$ °C. However, many of the models simulated the yield decline due to increasing temperatures within the measurement errors (±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[2,15]. 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[16]. Lack of such information can affect the outcomes of an impact assessment owing to large model input uncertainties[2]. 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 inbuilt 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[17] 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 °C in temperature and between 6% and 55% across sites with an increase of 4 °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[1] (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
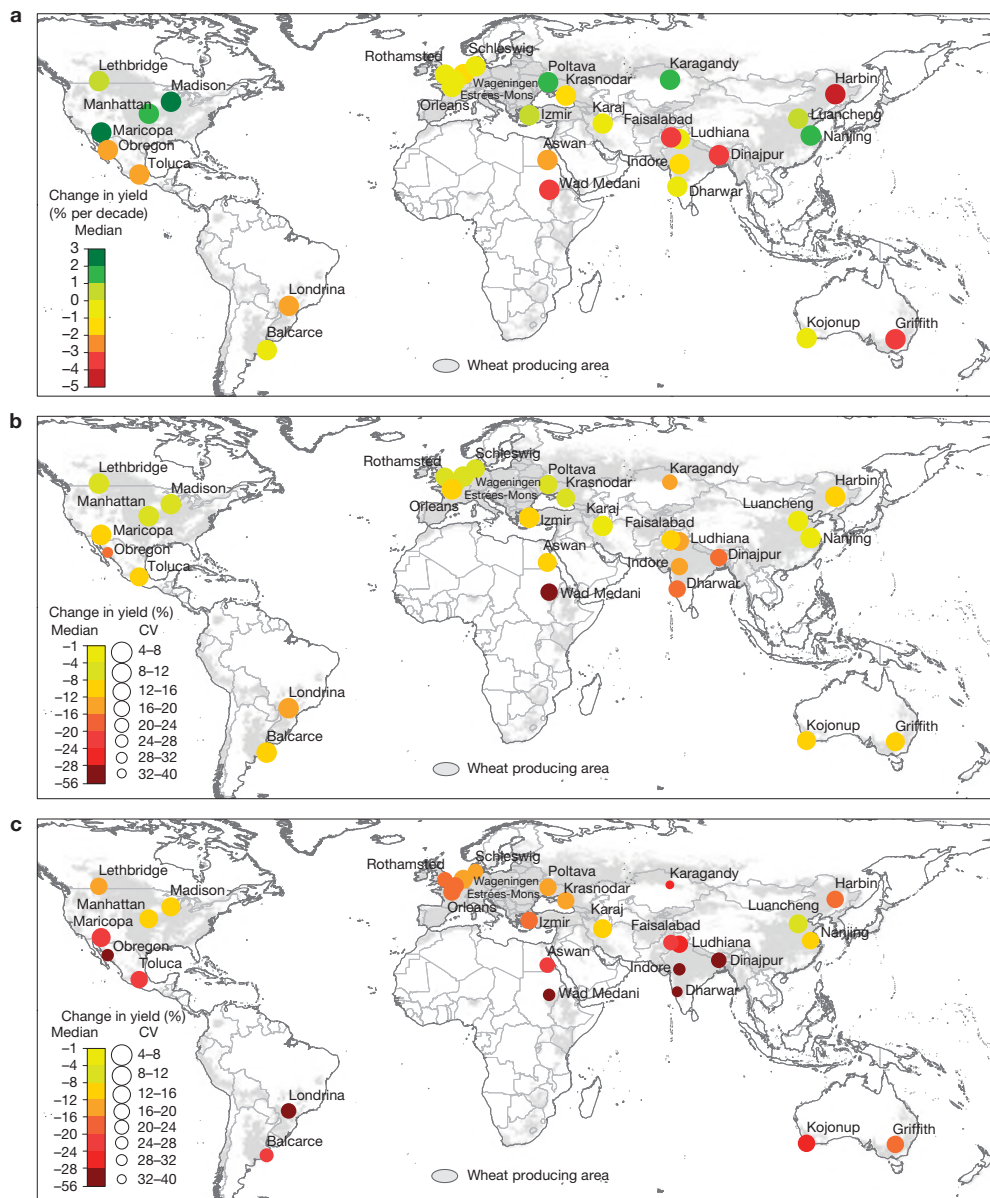
Figure 2 | Simulated global wheat grain yield change in the past and with higher temperatures. a, Grain yield trends for 1981–2010 based on the median yield of a 30-model ensemble. **b,c**, Relative median grain yield for +2 °C (**b**) and +4 °C (**c**) temperature increases imposed on the 1981–2010 period for the 30-model ensemble using region-specific cultivars. Simulation model uncertainty was calculated as the coefficient of variation (CV%) across 30 models and plotted as circle size. The larger the circle, the less the uncertainty.

critical economically as it could decrease some regional—and hence global—stability in wheat grain supply[18], amplifying market and price fluctuations[19].

About 70% of present global wheat production comes from irrigated or high rainfall regions[20]. 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[11]. 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[21]. However, other experimental evidence suggests that increased temperature

has negative impacts regardless of water[22] (Supplementary Figs 15 and 16) and N supply[23] (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[24] (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[25], 6% means a possible reduction of 42 Mt per °C of temperature increase. To put
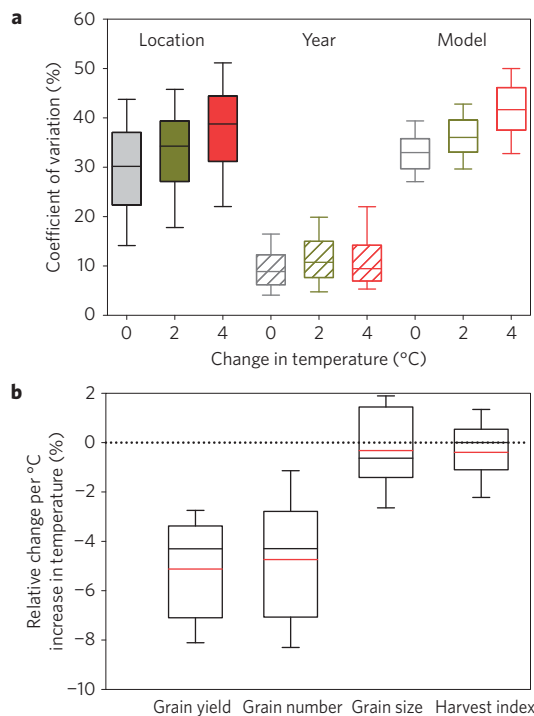
Figure 3 | Variability, uncertainty and causes of simulated wheat grain yield decline with increasing temperature. a, Coefficient of variation (%) for simulated grain yields according to location and year variability and model uncertainty. In each box plot, horizontal lines represent, from top to bottom, the 10th percentile, 25th percentile, median, 75th percentile and 90th percentile of 900 simulations for present climate (grey), +2 °C (green) and +4 °C (red). **b,** Box plots of simulated multi-model ensemble medians (of 30 models) of 30-year averages for each location of relative change in grain yield, grain number, grain size and harvest index per °C increase. Red lines indicate the simulated mean for 30 locations (not weighted for cropping area). Zero is indicated as a dotted line.

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[21,26] and a recent multi-model global gridded impact assessment which considered several climate factors together[8], 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[1] 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[27] 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[28] (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[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[29]. 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.

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Author contributions

S.A., F.E., P.M., R.P.R. and D.B.L. motivated the study, S.A. and F.E. coordinated the study, S.A., F.E., P.M., D.C., D.W. and P.D.A. analysed data, D.C., J.W.W., P.K.A., J.A., B.B., C.B., A.J.C., G.D.S., J.D., E.F., M.G-V., S.G., G.H., L.A.H., R.C.I., M.J., C.D.J., K.C.K., A-K.K., C.M., S.N.K., C.N., G.O'L., J.E.O., T.P., E.P., E.E.R., M.A.S., I.Shcherbak, C.S., P.S., T.S., I.Supit, F.T., P.J.T., K.W., E.W., J.W., Z.Z. and Y.Z. carried out crop model simulations and discussed the results, B.A.K., M.J.O., G.W.W., J.W.W., M.P.R., P.D.A., P.V.V.P. and A.C.R. provided experimental data, S.A., F.E., P.M., R.P.R., D.B.L., B.A.K., A.J.C., J.W.W., M.P.R., C.M., A.C.R., M.A.S. and D.W. wrote the paper.

Competing financial interests

The authors declare no competing financial interests.

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