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Rising temperatures reduce global wheat production

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Crop models are essential tools for assessing the threat of climate change on local and global food production[1]. Current 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.

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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 has been tested systematically against experiments at different temperatures in field conditions. While 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 climate change impacts 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 28°C (Fig. 1A, B). Performance of individual models is illustrated in Supplementary Fig. S3. Note that simulations were carried out in a 'blind' test (modelers had access to phenology and yield data of one of the treatments only (normal temperature); see Supplementary Materials). Higher temperatures thus decreased the number of days during which plants could intercept light for photosynthesis with consequent reductions in biomass (Supplementary Fig. S5) and grain yields (Fig. 1).When T_{mean} >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 yields were zero (Fig. 1A to C and Supplementary Fig. S6A to C). Observed grain yields declined from about 8 t/ha when T_{mean} was 15°C to zero when T_{mean} was 32°C (Fig. 1C and Supplementary Fig. S6C). Many wheat models simulated the observed anthesis and maturity dates and grain yields when the T_{mean} was between 15°C and 20°C. However, when T_{mean} reached about 22°C, observed grain yield measurements were more variable, i.e. 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 (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. S7). 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 Figure S5A) and yield well (Fig. 1). However, unexplained differences between simulations and some observed yields also exist at around 15 ^oC where some of the experimental errors are also large (Fig 1C). At seasonal mean temperature of 28 ^oC the observed yield was zero and a few models that included heat stress routines affecting canopy senescence, but not necessarily, were able to simulate a zero or close-to-zero yield (Supplementary Fig. S6C). At a seasonal mean temperature >30 ^oC, the multi-model ensemble median represented the observed zero yields well.

A second experimental data set was analyzed 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 simulations showed the same temperature responses. However, unlike the HSC experiment, crops did not fail with T_{mean} >28^oC and still yielded about 2 t/ha of grain. This was despite similar T_{max} in both experiments during the time after sowing and before the HSC crop died (i.e. about 28 DAS; Supplementary Fig. S8). The cultivars Bacanora (Fig. 1D-F) and Nesser (Supplementary Fig. S9) used in the CIMMYT experiments in various locations might be more heat tolerant than 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].

[Insert Figure 1 here]

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^oC. 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 current 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 modeling studies is sparse[16]. Lack of such information can affect the outcomes of an impact assessment due to large model input uncertainties[2]. Here, additional information on cultivar parameters and phenology improved grain yield simulations for a few individual models (Supplementary Table S4), 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. S10). 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”, modelers were asked to fix their simulated anthesis and maturity dates as close as possible to the observed dates (i.e. root mean square relative error (RMSRE) for anthesis and maturity dates were close to zero (Supplementary Table S4)) 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. S10). In addition, small errors in simulated phenology did not necessarily translate into errors in yield particularly if there was compensation between the modeling 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 laterflowering 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 Fig. S11 to S13) due to positive temperature trends over the same period (Supplementary Fig. S1). 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^{o}C in temperature and between 6% and 55% across sites with an increase of 4^{o}C (Fig 2B, C).

[Insert Figure 2 here]

For locations at low latitudes increase in simulated yield variability with higher temperature was more marked than at high latitudes, because the relative yield decline was greater due to the higher reference temperatures[1] (Fig. 2C). However, yield variability expressed in absolute terms hardly changed (Supplementary Fig. S14). Similarly, the year-to-year variability increased at some locations with temperature increases because of greater relative yield reductions in warmer years and lesser ones 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[18], amplifying market and price fluctuations[19].

[Insert Figure 3 here]

About 70% of current 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 S3), 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 due to 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 rainfed and water and nitrogen limited conditions, it was found that seasonal temperature increases of up to 2^{o}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 Fig. S15 and S16) and N supply[23] (Supplementary Fig. S17). 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 (www.fao.org) and disaggregated global mean surface temperature increases to regional surface temperature changes[24] (see Supplementary Materials and Supplementary Table S3). For each ^{o}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 current global production of 701 Mt of wheat in 2012 (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 ^{o}C increase. To put this in perspective, the amount is equal to a quarter of global wheat trade which reached 147 Mt in 2013 (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 modeling 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 Table S1 and S2), were compared with two previously unpublished data sets from quality-assessed field experiments from sentinel sites (see Supplementary Materials) within the Agricultural Model Intercomparison and Improvement Project[28] (AgMIP; 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 Materials). Model simulations were executed by individual modeling groups.

References

1. Challinor, A.J. et al. A meta-analysis of crop yield under climate change and adaptation. Nature Climate Change **4**, 287-291 (2014).
2. Asseng, S. et al. Uncertainty in simulating wheat yields under climate change. Nature Climate Change **3**, 827-832 (2013).
3. Godfray, H.C.J. et al. Food Security: The Challenge of Feeding 9 Billion People. Science **327**, 812-818 (2010).
4. Reynolds, M.P., Hays, D. & Chapman, S. Breeding for Adaptation to Heat and Drought Stress (ed. Reynolds, M.P.) (2010).
5. Asseng, S., Foster, I. & Turner, N.C. The impact of temperature variability on wheat yields. Global Change Biology **17**, 997-1012 (2011).
6. Gourdji, S.M., Sibley, A.M. & Lobell, D.B. Global crop exposure to critical high temperatures in the reproductive period: historical trends and future projections. Environmental Research Letters **8** (2013).
7. Teixeira, E.I., Fischer, G., van Velthuizen, H., Walter, C. & Ewert, F. Global hot-spots of heat stress on agricultural crops due to climate change. Agricultural and Forest Meteorology **170**, 206-215 (2013).
8. Rosenzweig, C. et al. Assessing agricultural risks of climate change in the 21st century in a global gridded crop model intercomparison. Proceedings of the National Academy of Sciences of the United States of America **111**, 3268-73 (2014).
9. van Herwaarden, A.F., Richards, R.A., Farquhar, G.D. & Angus, J.F. 'Haying-off', the negative grain yield response of dryland wheat to nitrogen fertiliser - III. The influence of water deficit and heat shock. Australian Journal of Agricultural Research **49**, 1095-1110 (1998).
10. Ewert, F. et al. Effects of elevated CO2 and drought on wheat: testing crop simulation models for different experimental and climatic conditions. Agriculture Ecosystems & Environment **93**, 249-266 (2002).
11. Ottman, M.J., Kimball, B.A., White, J.W. & Wall, G.W. Wheat Growth Response to Increased Temperature from Varied Planting Dates and Supplemental Infrared Heating. Agronomy Journal **104**, 7-16 (2012).
12. Wall, G.W., Kimball, B.A., White, J.W. & Ottman, M.J. Gas exchange and water relations of spring wheat under full-season infrared warming. Global Change Biology **17**, 2113-2133 (2011).
13. Porter, J.R. & Gawith, M. Temperatures and the growth and development of wheat: a review. European Journal of Agronomy **10**, 23-36 (1999).
14. Amani, I., Fischer, R.A. & Reynolds, M.P. Canopy temperature depression associated with yield of irrigated spring wheat cultivars in a hot climate. Journal of Agronomy & Crop Science **176**, 119-129 (1996).
15. Bassu, S. et al. How do various maize crop models vary in their responses to climate change factors? Global Change Biology **20**, 2301-2320 (2014).
16. Bondeau, A. et al. Modelling the role of agriculture for the 20th century global terrestrial carbon balance. Global Change Biology **13**, 679-706 (2007).
17. Fischer, R. Growth and water limitation to dryland wheat yield in Australia - Physiological framework. Journal of the Australian Institute of Agricultural Science **45**, 83-94 (1979).

18. Iizumi, T. et al. Prediction of seasonal climate-induced variations in global food production. Nature Climate Change **3**, 904-908 (2013).
19. Hertel, T.W., Burke, M.B. & Lobell, D.B. The poverty implications of climate-induced crop yield changes by 2030. Global Environmental Change-Human and Policy Dimensions **20**, 577-585 (2010).
20. Reynolds, M. & Braun, H. in Proceedings of the 3rd International Workshop of Wheat Yield Consortium (eds. Reynolds, M. & Braun, H.) ix-xi (CIMMYT, CENEB, CIMMYT, Obregon, Sonora, Mexico, 2013).
21. van Ittersum, M.K., Howden, S.M. & Asseng, S. Sensitivity of productivity and deep drainage of wheat cropping systems in a Mediterranean environment to changes in CO2, temperature and precipitation. Agriculture Ecosystems & Environment **97**, 255-273 (2003).
22. Pradhan, G.P., Prasad, P.V.V., Fritz, A.K., Kirkham, M.B. & Gill, B.S. Effects of drought and high temperature stress on synthetic hexaploid wheat. Functional Plant Biology **39**, 190-198 (2012).
23. Mitchell, R.A.C., Mitchell, V.J., Driscoll, S.P., Franklin, J. & Lawlor, D.W. Effects of increased CO_2 concentration and temperature on growth and yield of winter-wheat at 2 levels of nitrogen application. Plant Cell and Environment **16**, 521-529 (1993).
24. Collins, M. et al. Long-term Climate Change: Projections, Commitments and Irreversibility. Intergovernmental Panel on Climate Change, 108 (2013).
25. Nelson, G.C. et al. Climate change effects on agriculture: Economic responses to biophysical shocks. Proceedings of the National Academy of Sciences **111**, 3274-3279 (2014).
26. Nelson, G.C. et al. Climate change: Impact on agriculture and costs of adaptation. IFPRI Food Policy Report **21** (2009).
27. Cossani, C.M. & Reynolds, M.P. Physiological traits for improving heat tolerance in wheat. Plant Physiol **160**, 1710-8 (2012).
28. Rosenzweig, C. et al. The Agricultural Model Intercomparison and Improvement Project (AgMIP): Protocols and pilot studies. Agricultural and Forest Meteorology **170**, 166-182 (2013).
29. Reynolds, M.P., Balota, M., Delgado, M.I.B., Amani, I. & Fischer, R.A. Physiological and morphological traits associated with spring wheat yield under hot, irrigated conditions. Australian Journal of Plant Physiology **21**, 717-730 (1994).

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Figure captions

Figure 1 | Observations and multi-model simulations of wheat phenology and grain yields at different mean seasonal temperatures. (**A** to **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 gray) based on 30 simulation models are shown. (**A** to **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** to **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 ^{o}C in A and B due to premature death of crops. For details of field experiments and calibration steps, see Supplementary Materials. Error bars are not shown when smaller than symbol.

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. Relative median grain yield for (**B**) +2^{o}C and (**C**) +4^{o}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.

Figure 3 | Variability, uncertainty and causes of simulated wheat grain yield decline with increasing temperature. (**A**) Coefficient of variation (CV%) 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 current climate (grey), +2^{o}C (green) and +4 ^{o}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 ^{o}C increase. Red lines indicate the simulated mean for 30 locations (not weighted for cropping area). Zero is indicated as dotted line.