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Uncertainty in simulating wheat yields under climate change

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Projections of climate change impacts on crop yields are inherently uncertain[1]. Uncertainty is often quantified when projecting future greenhouse gas emissions and their influence on climate[2]. However, multi-model uncertainty analysis of crop responses to climate change is rare because systematic and objective comparisons among process-based crop simulation models[1,3] are difficult[4]. Here we present the largest standardized model intercomparison for climate change impacts so far. We found that individual crop models are able to simulate measured wheat grain yields accurately under a range of environments, particularly if the input information is sufficient. However, simulated climate change impacts vary across models owing to differences in model structures and parameter values. A greater proportion of the uncertainty in climate change impact projections was due to variations among crop models than to variations among downscaled general circulation models. Uncertainties in simulated impacts increased with CO_2 concentrations and associated warming. These impact uncertainties can be reduced by improving temperature and CO_2 relationships in models and better quantified through use of multi-model ensembles. Less uncertainty in describing how climate change may affect agricultural productivity will aid adaptation strategy development and policymaking.

Uncertainties in projections of climate change impacts on future crop yields derive from different sources in modelling. The trajectories of future greenhouse gas emissions cannot be projected easily as they are strongly influenced by political and socio-economic development. A range of plausible projections (scenarios) of emissions are used instead[2]. Projecting the effects of emissions on climate and the downscaling of climate data themselves, are both inherently uncertain, because different general circulation model ensembles[5] and downscaling methods[6] give different results. Finally, uncertainty in simulating the response of crops to altered climate can be attributed to differences in the structures of crop models and how model parameters are set. Process-based crop models account for many of the interactions among climate, crop, soil and management effects and are the most common tools for assessing climate change impacts on crop productivity. Many crop model impact assessments have been carried out for specific locations[7], agricultural regions[8] and the globe[9]. Statistical methods have also been used to analyse trends in yields driven by climate[10], but interactions between climate and non-climate factors confound results[11]. This hinders the attribution of causality[12] and development of appropriate adaptation strategies.

Uncertainty, any departure from the unachievable ideal of completely deterministic knowledge of a system[13], has been addressed by the climate science community through probabilistic projections based on multiple general circulation models (GCMs) or regional climate model ensembles[14]. However, most climate change agricultural impact assessments have used a single crop model[3], limiting the quantification of uncertainty[15]. As crop models differ in the way they simulate dynamic processes, set parameters and use input variables[3], large differences in simulation results have been reported[16]. Although uncertainty of crop model projections is sometimes assessed by using more than one crop model[16] or by perturbing crop model parameters[17], coordinating comprehensive assessments has proved difficult[4].

To estimate the uncertainty associated with studies of climate impacts on crop yields, we used 27 different wheat crop models (Supplementary Tables S1 and S2) at four sites representing very different production environments (Fig. 1a). Simulated grain yields varied widely, although median values were close to observed grain yields across single-year experiments for four representative environments (Supplementary Table S3) in the Netherlands, Argentina, India and Australia (Fig.1a, b). This phenomenon was previously reported in another multi-model comparison with fewer models[16], and is comparable to the improved seasonal climate simulations produced with multiple GCMs (ref. 18). The range of simulated yields was reduced significantly after full calibration, such that >50% of yields from calibrated models were within the mean coefficient of variation (CV%) (±13.5%) of >300 wheat field experiments[19] (Fig. 1c). Similar patterns were found for other simulated aspects of wheat growth (Fig. 1d). Hence, crop models are able to simulate measured grain yield and other crop components accurately under diverse environments if input information is sufficient.

To illustrate the possible changes in uncertainty of simulated impacts, we analysed the sensitivity of models to a combination of changes in precipitation and increases in both temperature and atmospheric CO_2 concentration (734 ppm, compared with baseline at 360 ppm) based on a location-specific scenario that best approximated the ensemble of high-emission late-century climate projections (Supplementary Table S3). Simulated climate change yield responses of all partially calibrated crop models had CV values between 20 and 30% (Fig. 2a); these were reduced by 2–7% when models were fully calibrated. However, the CV of simulated impacts using the 50% best-performing calibrated models (based on root mean square errors (r.m.s.e) across all locations) was about 2% higher than using all models, and this decreased only when the 50% of models closest to observed yields at each location were used (Fig. 2a). Uncertainty in simulated climate change impacts differed across the environments (Fig. 2a). In addition, uncertainty in simulated impacts varied with soil (Fig. 2b) and crop management (Fig. 2c,d). Hence, the overall

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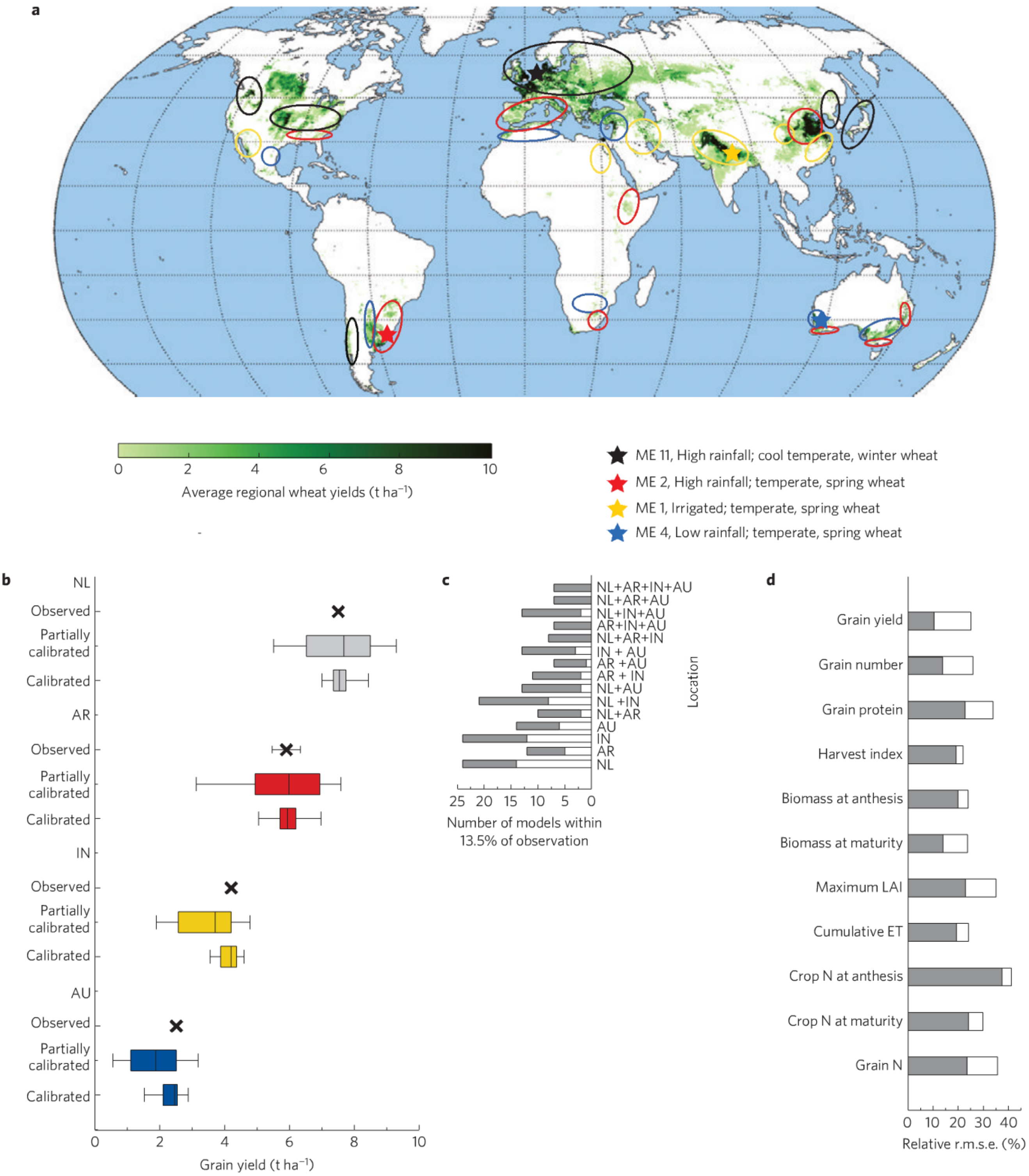

Figure 1 | Wheat model–observation comparisons. a, Global map of wheat production[30] showing experimental sites (stars) representative of CIMMYT mega-environments (ME, broadly indicated by ovals, http://wheatatlas.cimmyt.org). **b**, Observed (cross mark) and simulated (box plots) grain yields from single-year experiments for the Netherlands (NL), Argentina (AR), India (IN) and Australia (AU). Simulated yields are from 27 different wheat crop models. Partially calibrated simulated yields (larger boxes)—researchers had no access to observed grain yields and growth dynamics (blind test). Calibrated simulated yields (smaller boxes)—researchers had access to observed grain yields and growth dynamics. In each box plot, vertical lines represent, from left to right, the 10th percentile, 25th percentile, median, 75th percentile and 90th percentile of simulations. Standard deviation for observed yields (based on measurements of four replicates) is shown as an error bar if known. **c**, Number of models within mean field experimental variation (13.5%; ref. 19) for partially calibrated (open bars) and fully calibrated models (grey bars) for single locations (NL, AR, IN and AU for each country) and combinations of locations. **d**, Relative r.m.s.e. of simulation–observation comparisons for partially calibrated (open bar) and fully calibrated models (grey bars) of grain yield components across all four locations. LAI, leaf area index; ET, evapotranspiration.

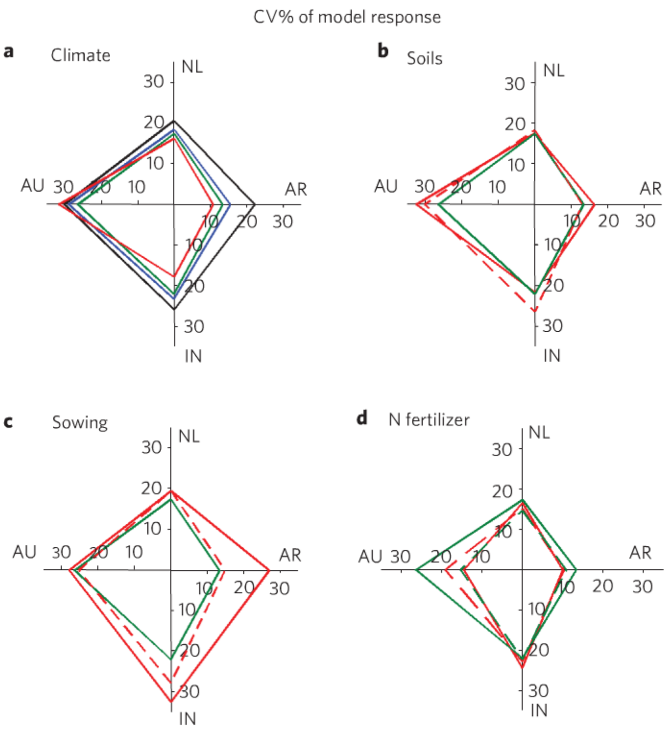

Figure 2 | Variability in impact model uncertainty. a, CV% for simulated yield response to a location-specific scenario representing GCM projections for the high-emission (A2) scenario for the late century (in relation to baseline 1981–2010, Supplementary Table S3) with 27 crop models. Models were partially calibrated (black) or fully calibrated (green). In addition, 50% of models with the closest simulations to the observed yields across all locations (blue) and 50% of models with the closest simulations to the observed yields per location are shown (red). **b–d**, CV% of simulated yield response to the climate change scenario with 27 fully calibrated crop models with increased (solid red) and reduced (dashed red) soil water holding capacity (**b**), early (solid red) and delayed (dashed red) sowing dates (**c**) and increased (solid red) and reduced (dashed red) N fertilizer applications (**d**; only 20 models included N dynamics); fully calibrated 20 models that included N dynamics (dashed green). The fully calibrated simulation (green) from **a** is reproduced in **b–d** for comparison. The Netherlands (NL), Argentina (AR), India (IN) and Australia (AU).

growing environment, in particular the soil and crop management, affects the range of simulated grain yields across models, thus adding to uncertainty in responses coming from individual models. Therefore, selecting a subset of models that perform best in present environments does not reduce uncertainty in simulated climate change impacts.

Changes in atmospheric CO_2, temperature and precipitation are key drivers of the responses of crops to climate change[20]. Simulated impacts of elevated CO_2 on yields varied relatively little across models (50% of model results were within ±20% of the median response; Fig. 3a–d and Supplementary Fig. S5), but the variation across 80% of the crop models increased under elevated CO_2 concentration mostly in the low-yielding environment of Australia (see box-plot whiskers in Fig. 3d). The uncertainty in simulated yields did not increase with increasing CO_2 in the other environments. This is not surprising as elevated CO_2 affects fewer processes than increased temperature and because several of the wheat models have used observations from free-air CO_2 enrichment experiments to improve model processes related to high CO_2 (refs 21,22). However, none of the models has been tested with elevated CO_2 in combination with high temperature. Most simulated yield responses to a 180 ppm CO_2 increase at present temperatures (Fig. 3a–d) were within the range of measured responses, ranging from 8% to 26% with elevated atmospheric CO_2 concentrations (Fig. 3e) across experiments conducted in the USA, Germany and China[23,24] (Supplementary Information, page 11 last paragraph).

In contrast to the mean response of yields to CO_2, uncertainty in simulated yield showed a strong dependency on temperature, particularly when the temperature increase exceeded 3 °C with associated changes in atmospheric CO_2. The median model response to a 3 °C increase in temperature (Fig. 3a–d and Supplementary Fig. S5) is consistent with general field observations (Fig. 3e); observed wheat grain yields declined by 3–10% $^{\circ}C^{-1}$ increase in mean temperature[10,24] (Supplementary Information, page 11 last paragraph). The increased range of impacts at high temperatures (50% of models were between 20 and 40% of the median response on either side) indicated an increased model uncertainty with increasing temperature. This is partly related to simulated phenology (Supplementary Fig. S3). For example, phenology is often enhanced with increasing temperature resulting in less time for light interception and photosynthesis and consequently less biomass and yield. In addition, the increased model uncertainty is also partly due to an increased frequency of high-temperature events and its simulated impact on crop growth[25] (Supplementary Fig. S4), and high-temperature interactions with elevated CO_2 (Fig. 3). However, accounting for a process such as high-temperature stress impact in a model does not necessarily result in correctly simulating that effect (Supplementary Fig. S4), as the modelled process itself, for example, leaf area or biomass growth, interacts with other model processes in determining the final yield response of a model. Precipitation affected simulated yields, but precipitation change had little impact on the range of simulated responses (Supplementary Fig. S2).

If averaging multi-model simulations is superior to a single crop[4] or climate[26] model simulation because the ratio of signal (mean change) to noise (variation) increases with the number of models and errors tend to cancel each other out, we should be able, with caution[27], to estimate how many models would be required for robust projections. We assessed this by randomly choosing 260 subsets of the crop models, and computing the mean and spread of simulated results (Supplementary Fig. S1). As the variation in yields was about 13.5% around the mean in field experiments[19], we considered projections to be robust if the range of projections was within 13.5% of the mean. The number of models required for robust assessments of climate change varied depending on the magnitude of temperature change and interactions with the change in atmospheric CO_2 (Fig. 4a). For example, at least five models are needed for robust assessments of yield impacts for increases of up to 3 °C and 540 ppm of CO_2. Fewer models are needed for smaller changes and more models for greater changes in temperature (Fig. 4a).

When simulating impacts assuming a mid-century A2 emissions scenario (556 ppm of CO_2) for climate projections from 16 downscaled GCMs using 26 wheat models, a greater proportion of the uncertainty in yields was due to variations among crop models than to variations among the downscaled GCMs (Fig. 4b). In contrast, GCM uncertainty tends to dominate in perturbed single crop model parameter studies[28]. The variation of simulated yields for the scenario ensemble was greater for low-yielding environments and absolute values were similar to observations across yield levels and within the range of field experimental variation[19]. Smaller projected climate changes, for example, for low emissions or early-century time frames, result in less variation in simulated impacts; larger climate changes result in more variation (Fig. 3).

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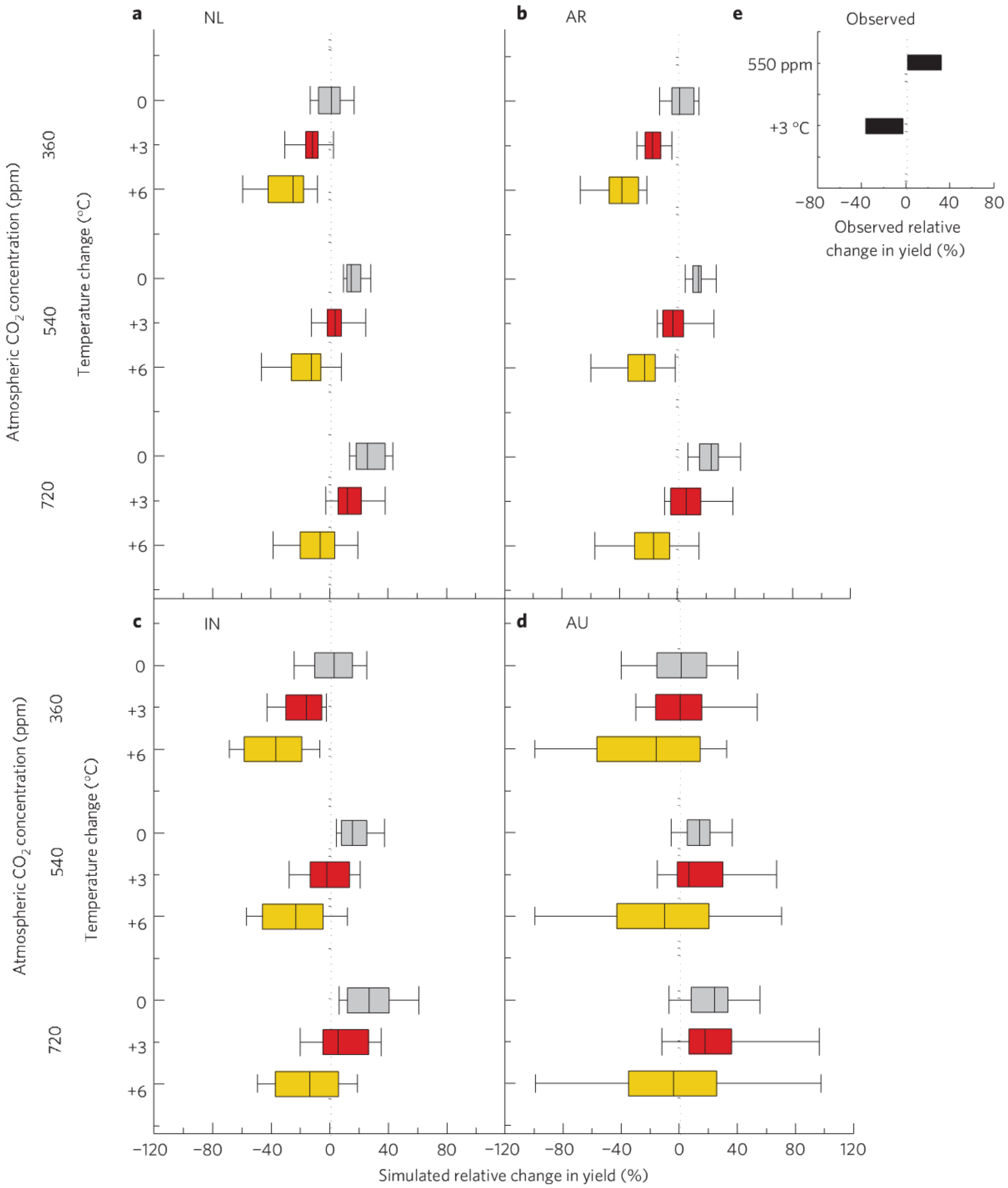

Figure 3 | Sensitivity of simulated and observed wheat to temperature and CO_2 change. a–d, Simulated relative mean (30-year average, 1981–2010) grain yield change for increased temperatures (no change, grey; +3 °C, red; +6 °C, yellow) and elevated atmospheric CO_2 concentrations for the Netherlands (NL; **a**), Argentina (AR; **b**), India (IN; **c**) and Australia (AU; **d**). For each box plot, vertical lines represent, from left to right, the 10th percentile, 25th percentile, median, 75th percentile and 90th percentile of simulations based on multi-models. **e**, Observed range of yield impacts with elevated CO_2 (refs 23,24). Observed range of yield impacts with increased temperature[10,24] (extrapolated, based on separate experiments with 40–345 ppm elevated CO_2 and 1.4–4.0 °C temperature increase, Supplementary Information).

We conclude that projections from individual crop models fail to represent the significant uncertainties known to exist in crop responses to climate change. On the other hand, model ensembles have the potential to quantify the significant, and hitherto uncharacterized, crop component of uncertainty. Crop models need to be improved to more accurately reflect how heat stress and high-temperature-by-CO_2 interactions affect plant growth and yield formation.

Methods

Twenty-seven wheat crop simulation models (Supplementary Tables S1 and S2) were tested within the Agricultural Model Intercomparison and Improvement Project[29] (www.agmip.org), with data from quality-assessed field experiments (sentinel site data) from four contrasting environments using standardized protocols, including partial and full model calibration experiments, to assess the role of crop model-based uncertainties in projections of climate change impacts (Fig. 1a and Supplementary Information). Model simulations were executed by individual modelling groups.

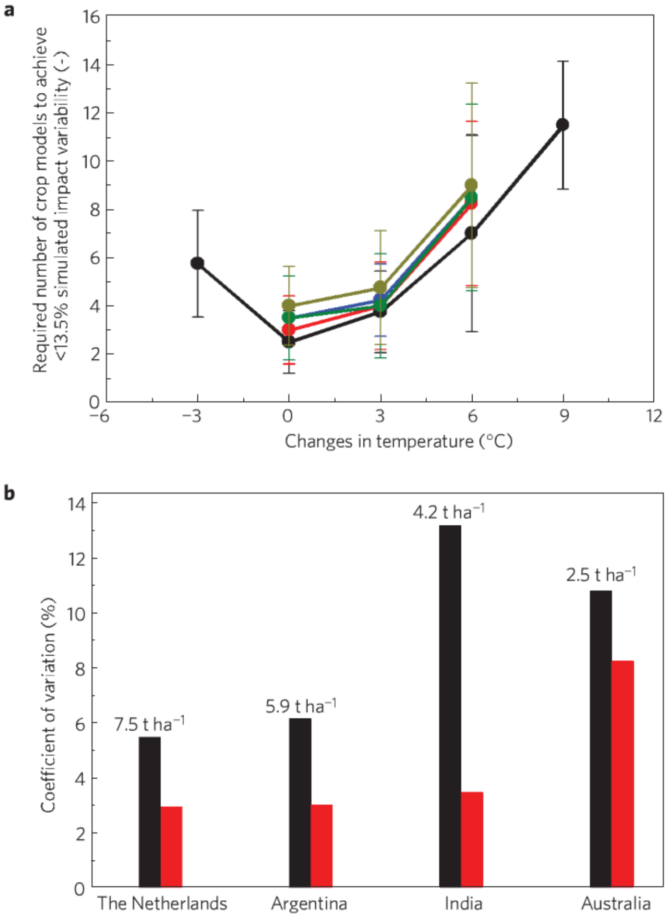

Figure 4 | Size of model ensembles and impact model uncertainty. **a**, Average number of crop models across locations required to reduce the simulated yield impact variation to within the mean field experimental CV% of 13.5% (ref. 19). Different colours indicate elevated atmospheric CO_2 concentrations (black, 360 ppm; red, 450 ppm; blue, 540 ppm; green, 630 ppm; dark yellow, 720 ppm) in combinations with temperature changes. Error bars show s.d. **b**, CV due to crop model uncertainty (using 10th percentile to 90th percentile of simulations based on 26 crop models) in simulated 30-year average climate change yield impact (black) and due to variation in 16 downscaled GCM (red, Supplementary Tables S6 and S7) mid-century A2 emission scenarios (2040–2069). Numbers indicate present yields at each location (Supplementary Table S3).

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Author contributions

S.A., F.E., C.R., J.W.J., K.J.B. and J.L.H. motivated the study; S.A. and F.E. coordinated the study; S.A., F.E., D.W., P.M., D.C. and A.C.R. analysed data; D.C., A.C.R., K.J.B., P.J.T., R.P.R., N.B., B.B., D.R., P.B., P.S., L.H., M.A.S., P.S., C.S., G.O.L., P.K.A., S.N.K., R.C.I., J.W.W., L.A.H., R.G., K.C.K., T.P., J.H., T.O., J.W., I.S., J.E.O., J.D., C.N., S.G., J.I., E.P., T.S., F.T., C.M., K.W., R.G., C.A., I.S., C.B., J.R.W. and A.J.C. carried out crop model simulations and discussed the results; M.T. and S.N.K., provided experimental data; S.A., F.E., C.R. and J.W.J. wrote the paper.

Additional information

Supplementary information is available in the online version of the paper. Reprints and permissions information is available online at www.nature.com/reprints. Correspondence and requests for materials should be addressed to S.A.

Competing financial interests

The author declares no competing financial interests.

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Supplementary Information

Supplementary Materials and methods

Partially and fully calibrated simulation experiments (Fig. 1 and 2) with observed field experimental data

Twenty-seven different wheat crop simulation models were used by individual modeling groups (in most cases by the model developers) (Supplementary Table S1) for a model intercomparison. The models varied in complexity and functionality (Supplementary Table S2). Six models did not simulate nitrogen (N) dynamics (Supplementary Table S2). Simulations were carried out for single treatments of experiments at four contrasting locations, which were The Netherlands (Wageningen[1]), Argentina (Balcarce[2]), India (New Delhi[3]), and Australia (Wongan Hills[4]) (Supplementary Table S3) representing a very wide range of growing conditions of wheat. Crop management treatments were chosen to be representative for each region (Supplementary Table S3).

Supplementary Table S1. Crop models (27) used in AgMIP Wheat study.

odel (version)	Reference	Documentation
PSIM-Nwheat (V.1.55)	4-6	http://www.apsim.info
SIM (V.7.3)	6	http://www.apsim.info/Wiki/
uaCrop (V.3.1+)	7	http://www.fao.org/nr/water/aquacrop.html
opSyst (V.3.04.08)	8	http://www.bsyse.wsu.edu/CS_Suite/CropSyst/index.html
SAT- CERES (V.4.0.1.0)	9, 10, 11	http://www.icasa.net/dssat/
SAT-CROPSIM (V4.5.1.013)	10, 12	http://www.icasa.net/dssat/

Ecosys	13	https://portal.ales.ualberta.ca/ecosys/
EPIC wheat (V1102)	14-16	http://epicapex.brc.tamus.edu/
Expert-N (V3.0.10) - CERES (V2.0)	17-20	http://www.helmholtz-muenchen.de/en/iboe/expertn/
Expert-N (V3.0.10) – GECROS (V1.0)	19, 20	http://www.helmholtz-muenchen.de/en/iboe/expertn/
Expert-N (V3.0.10) – SPASS (2.0)	17, 19-22	http://www.helmholtz-muenchen.de/en/iboe/expertn/
Expert-N (V3.0.10) - SUCROS (V2)	17, 19, 20, 23	http://www.helmholtz-muenchen.de/en/iboe/expertn/
FASSET (V.2.0)	24, 25	http://www.fasset.dk
GLAM-wheat (V.2)	26, 27	http://see-web-01.leeds.ac.uk/research/icas/climate_change/glam/download_glam.html
HERMES (V.4.26)	28, 29	http://www.zalf.de/en/forschung/institute/lsa/forschung/oekomod/hermes
InfoCrop (V.1)	30	http://www.iari.res.in
LINTUL-4 (V.1)	31, 32	http://models.pps.wur.nl/models
LINTUL-FAST (V.1)	33	Request from frank.ewert@uni-bonn.de
LPJmL (V3.2)	34-39	http://www.pik-potsdam.de/research/projects/lpjweb
MCWLA-Wheat (V.2.0)	40-42 43	Request from taofl@igsnrr.ac.cn
MONICA (V.1.0)	44	http://monica.agrosystem-models.com
O'Leary-model (V.7)	45-48	Request from gjoleary@yahoo.com
SALUS (V.1.0)	49, 50	http://www.salusmodel.net
Sirius (V2010)	51-54	http://www.rothamsted.ac.uk/mas-models/sirius.php
SiriusQuality (V.2.0)	55-57	Request from pierre.martre@clermont.inra.fr
STICS (V.1.1)	58, 59	http://www.avignon.inra.fr/agroclim_stics_eng/
WOFOST (V.7.1)	60	http://www.wofost.wur.nl

Supplementary Table S2. Modeling approaches of 27 wheat simulation models used in AgMIP wheat study.

Model	Leaf area / light interception [a]	Light utilization [b]	Yield formation [c]	Phenology [d]	Root distribution over depth [e]	Environmental constraints involved [f]	Type of water stress [g]	Type of heat stress [h]	Water dynamics [i]	Evapotranspiration [j]	Soil CN-model [k]	Process modified by elevated CO_2 [l]	No. cultivar parameters	Climate input variables [m]	Model relative [n]
APSIM-Nwheat	S	RUE	Prt	T/DL/V	EXP	W/N/A	S	V	C	PT	CN/P(3)/B	RUE/TE	7	R/Tx/Tn/Rd	C
APSIM-wheat	S	RUE	Prt/Gn/B	T/DL/V/O	O	W/N/A	E	-	C/R	**PT**/PM	CN/P(3)/B	RUE/TE/CLN	7	R/Tx/Tn/Rd/e/W	C
AquaCrop	S	TE	HI/B	T/DL/V/O	EXP	W/N/H	E/S	V/R	C	PM	none	TE	2	R/Tx/ETo	none
CropSyst	S	TE/RUE	HI/B	T/DL/V	EXP	W/N/H	E	R	C/R	PM	N/P(4)	TE/RUE	16	R/Tx/Tn/Rd/RH/W	none
DSSAT-CERES	S	RUE	B/Gn	T/DL/V	EXP	W/N	E/S	-	C	PT	CN/P(4)/B	RUE/TE	7	R/Tx/Tn/Rd/RH/W	C
DSSAT-CROPSIM	S	RUE	Prt	T/DL/V	LIN	W/N	E/S	V	C	PT	CN/P(4)/B	RUE/TE	21	R/Tx/Tn/Rd/	none
Ecosys	D	P-R	Gn-Prt	T/DL/V/O	Call	W/N/A/H	E/S	V/R	R	EB	P30/B5	F	2	R/Tx/Tn/Td/Rd/W	none
EPIC wheat	S	RUE	HI	T/V	EXP	W/N/H	E	V	C	P/**PM**/P T/HAR	N/P(5)/B	RUE/TE/GY	16	R/Tx/Tn/Rd/RH/W	E
Expert-N – CERES	S	RUE	B/Gn	T/DL/V	EXP	W/N	E/S	-	R	PM	CN/P(3)/B	RUE	7	R/Tx/Tn/Rd/RH/W	C
Expert-N – GECROS	D	P-R/TE	Gn/Prt	T/DL/V	EXP	W/N	E/S	-	R	PM	CN/P(3)/B	RUE/TE	10	R/Tx/Tn/Rd/RH/W	S
Expert-N – SPASS	D	P-R	Gn/Prt	T/DL/V	EXP	W/N	E/S	-	R	PM	CN/P(3)/B	RUE	5	R/Tx/Tn/Rd/RH/W	C/S
Expert-N – SUCROS	D	P-R	Prt	T	EXP	W/N	E/S	-	R	PM	CN/P(3)/B	RUE	2	R/Tx/Tn/Rd/RH/W	S
FASSET	D	RUE	HI/B	T/DL	EXP	W/N	E/S	-	C	MAK	CN/P(6)/B	RUE	14	R/Tx/Tn/Rd	none
GLAM-Wheat	S	RUE/TE	B/HI	T/DL/V	LIN	W/H	E	R	C	PT	none	RUE/TE	22	R/Tx/Tn/Td/Ta/e	none
HERMES	D	P-R	Prt	T/DL/V/O	EXP	W/N/A	E/S	-	C	**PM**/TW/ PT	N/P(2)	RUE/F	6	R/Tx/Tn/Rd/e/RH/W	S/C
InfoCrop	D	RUE	Prt/Gn	T/DL	EXP	W/N/H	E	V/R	C	**PM**/PT	CN/P(2)/B	RUE/TE	10	R/Tx/Tn/Rd/W/e	S
LINTUL-4	D	RUE	Prt/B	T/DL	LIN	W/N/A	E	-	C	P	N/P(0)*	RUE/TE	4	R/Tx/Tn/Rd/e/W	L
LINTUL-FAST	D	RUE	Prt	T/DL/V	EXP	W	E	-	C	PM	CN/P(3)	RUE/TE	4	R/Tx/Tn/Rd/RH	L

LPJmL	S	P-R	HI_mws/B	T/V	EXP	W	E	-	C	PT	none	F	3	R/Ta/Rd/Cl	E
MCWLA-Wheat	S	P-R	HI/B	T/DL/V	EXP	W/H	E	V/ R	R	PM	none	F	7	R/Tx/Tn/Rd/e/W	none
MONICA	S	RUE	Prt	T/DL/V/O	EXP	W/N/A/H	E	V	C	PM	CN/P(6)/B	F	15	R/Tx/Tn/Rd/RH/W	H
O'Leary-model	S	TE	Gn/Prt	T/DL	SIG	W/N/H	E/S	V	C	P	N/P(3)/B	TE	18	R/Tx/Tn/Rd/RH/W	none
SALUS	S	RUE	Prt/HI	T/DL/V	EXP	W/N/H	E	V	C	PT	CN/P(3)/B(2)	RUE	18	R/Tx/Tn/Rd	C
Sirius	D	RUE	B/Prt	T/DL/V	EXP	W/N	E	-	C	P/**PT**	N/P(2)	RUE	14	R/Tx/Tn/Rd/e/W	none
SiriusQuality	D	RUE	B/Prt	T/DL/V	EXP	W/N	S	-	C	**P**/PT	N/P(2)	RUE	14	R/Tx/Tn/Rd/e/W	I
STICS	D	RUE	Gn/B	T/DL/V/O	SIG	W/N/H	E/S	V/R	C	P/PT/ **SW**	N/P(3)/B	RUE/TE	15	R/Tx/Tn/Rd/e/W	C
WOFOST	D	P-R	Prt/B	T/DL	LIN	W/N*	E/S	-	C	P	P(1)	RUE/TE	3	R/Tx/Tn/Rd/e/W	S

[a] S, simple approach (e.g. LAI); D, detailed approach (e.g. canopy layers).
[b] RUE, radiation use efficiency approach; P-R, gross photosynthesis – respiration; TE, transpiration efficiency biomass growth.
[c] HI, fixed harvest index; B, total (above-ground) biomass; Gn, number of grains; Prt, partitioning during reproductive stages; HI_mw, harvest index modified by water stress.
[d] T, temperature; DL, photoperiod (day length); V, vernalization; O, other water/nutrient stress effects considered.
[e] LIN, linear, EXP, exponential, SIG, sigmoidal, Call, carbon allocation; O, other approaches.
[f] W, water limitation; N, N limitation; A, aeration deficit stress; H, heat stress.
[g] E, actual to potential evapotranspiration ratio; S, soil available water in root zone.
[h] V, vegetative organ (source); R, reproductive organ (sink).
[i] C, capacity approach; R, Richards approach.
[j] P, Penman; PM, Penman-Monteith; PT, Priestley –Taylor; TW, Turc-Wendling; MAK, Makkink; HAR, Hargreaves; SW, Shuttleworth and Wallace (resistive model); EB, energy balance ("bold" indicates approache used during the study).
[k] CN, CN model; N, N model; P(x), x number of organic matter pools; B, microbial biomass pool.
[l] RUE, radiation use efficiency; TE, transpiration efficiency; GY, grain yield; CLN, critical leaf N concentration; F, Farquhar model.
[m] Cl, cloudiness; R, precipitation; Tx, maximum daily temperature; Tn, minimum daily temperature; Ta, average daily temperature; Td, dew point temperature; Rd, radiation; e, vapor pressure; RH, relative humidity; W wind speed.
[n] C, CERES; L, LINTUL; E, EPIC; S, SUCROS; I, Sirius; H, HERMES.
[o] P, point model; G, global or regional model (regarding the main purpose of model).
* N-limited yields can be calculated for given soil N supply and N fertilizer applied, but model has no N simulation routines.

Supplementary Table S3. Field experiments, crop management and climate characteristics for baseline and a late century, high emission scenario (A2) used in partially calibrated and calibrated simulation experiments.

	Experiment			
	A[a]	**B**[b]	**C**[c]	**D**[d]
Location	Wageningen	Balcarce	New Delhi	Wongan Hills
Country	The Netherlands	Argentina	India	Australia
Latitude	51.97	-37.5	28.38	-30.89
Longitude	5.63	-58.3	77.12	116.72
Environment	high-yielding long-season	high/medium-yielding medium-season	irrigated short-season	low-yielding rain-fed short-season
Average growing season	November-July	June-December	November-April	May-December
Soils				
Soil type	Silty clay loam	Clay loam	Sandy loam	Loamy sand
Maximum Root depth (cm)	200	130	160	210
PAWC[†] (mm to maximum rooting depth)	354	205	121	125
Crop management				
Cultivar	Arminda	Oasis	HD 2009	Gamenya
Sowing date (DOY[‡])	294	223	328	164
Total applied N fertilizer (kg N/ha)	160	120	120	50
Total irrigation (mm)	0	0	383	0
Phenology				
Anthesis (DOY)	178	328	49	275
Maturity (DOY)	213	363	93	321
Experimental year	1982/83	1992	1984/85	1984
Mean growing season temperature	8.8 °C	13.7 °C	17.3 °C	14.0 °C
Mean growing season precipitation	595 mm	336 mm	383 mm[*]	164 mm
Baseline				
Mean growing season temperature	8.5 °C	12.0 °C	18.9 °C	16.2 °C
Mean growing season precipitation	716 mm	395 mm	467 mm*	246 mm
Climate change scenario[**]				
GCM scenario examined	ukmo_hadcm3	ncar_ccsm3.0	mpi_echam5	csiro_mk3.0
Mean growing season	11.4 °C	14.2 °C	23.6 °C	18.7 °C

temperature				
Mean growing season precipitation	690 mm	432 mm	583 mm*	164 mm

†Plant Available Water Content (PAWC, mm)

‡Day of Year (DOY)

* Includes 383 mm of irrigation each year

**A2 emission scenario from UKMO HadCM3 simulations, with 734 ppm CO_2 at 2085 was assumed in the climate model and the crop model simulations.

[a] Source: [1]

[b] Source: [2]

[c] Source: [3]

[d] Source: [4]

Sensitivity analysis with 30-years of climate data

In addition to simulations of the single-year experiments, simulations were carried out with long-term measured daily climate data (solar radiation, maximum and minimum temperature, precipitation, surface wind, dew point temperature, relative humidity, and vapor pressure) using measured soil characteristics, measured initial soil water and soil N contents, crop management, measured anthesis and maturity dates from the single-year-experiments. For the baseline, daily climate data for the period 1980-2010 were used for all locations (31 years of climate data are required to simulate 30 years of yields in The Netherlands and India). For the location in India, solar radiation was obtained from the NASA/POWER dataset that extends back to 1983 (http://power.larc.nasa.gov). Missing data for 1980 to 1983 were filled in using the Weatherman tool included in DSSAT 4.5[61]. In addition, 2-meter wind speed (m/s), dew point temperature (ºC), vapor pressure (hPa), and relative humidity (%) were estimated for each location from the NASA Modern Era Retrospective-Analysis for Research and Applications (MERRA[62]). For the location in The Netherlands, measured wind speed and vapor pressure were available.

Each of the 27 wheat models was used to simulate the field experiments in two separate steps, 1) with limited in-season information from the experiments being made available to the modelers (partial calibration or ‘blind’ simulations), and 2) all available information being made available to the modelers (full calibration). Simulations with partially calibrated models were included to allow a more objective model assessment[63]. For the partial calibration or ‘blind model test’, modelers had no access to measurements of grain yield, biomass, and crop water and N dynamics, receiving information only on soil characteristics, initial soil-water conditions, daily weather data, crop management, and flowering and maturity dates. For full calibration, modelers had access to all available measurements, including within-season and final biomass, water and N uptake, soil water and soil N, grain yield and yield components.

Note, some of these data may have been used, as part of a larger data set (NL and AU), for past calibration of some of the models. Furthermore, the organization of the project was such that one modeling group had access at all times to detailed data from all four sites, one group had access to NL and AU and one group had access to NL and did know the measurements beforehand. However, they did not change the model or parameters for the blind test as a consequence.

The annual simulation outputs included: grain yield (t ha^{-1}); above-ground biomass at anthesis (kg ha^{-1}); above-ground biomass at maturity (kg ha^{-1}); maximum leaf area index (LAI, m^2 m^{-2}); anthesis date (DOY); maturity date (DOY); cumulative N leached (kg N ha^{-1}); cumulative water loss (mm); total above-ground N at anthesis (kg N ha^{-1}); total above-ground N at maturity (kg N ha^{-1}); grain N (kg N ha^{-1}); grains per square meter (# m^{-2}); cumulative ET (mm); cumulative N mineralization (kg N ha^{-1}); cumulative N volatilization (kg N ha^{-1}); cumulative N immobilization (kg N ha^{-1}); cumulative N denitrification (kg N ha^{-1}); plant available soil water to maximum rooting depth (mm); soil mineral N to maximum rooting depth (kg N ha^{-1}).

Data analysis (Fig. 1, 2 and 3a-d)

The root mean square error (RMSE) between observed and simulated yield is calculated as:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}(y_i - \hat{y}_i)^2} \qquad (1)$$

where y_i are the measurements, $\hat{y}_i$the simulations, and n is the number of comparisons.

For the analysis in Fig. 1c, +/- 13.5% was used as the measurement uncertainty. That is the mean coefficient of variation (CV) for more than 300 wheat field experiments reported in Taylor et al. [64]. For Fig. 2a-d, we define model response to changed climate as:

$$x_k = \bar{y}_{future,k} - \bar{y}_{baseline,k} \qquad (2)$$

where x_k is predicted yield change according to model k, $\bar{y}_{future,k}$ is yield averaged over the 30 years of future climate according to model k and $\bar{y}_{baseline,k}$ is yield averaged over the 30 years of baseline climate according to model k. The coefficient of variation (CV%) of x represents the variation between models, calculated as:

$$CV\% = \frac{\sigma}{\bar{x}} * 100 \qquad (3)$$

where σ is the standard deviation of the yield changes (x) values and $\bar{x}$ is their average. Coefficients of variation were calculated separately for the partially calibrated models, the fully calibrated models, the 50% of fully calibrated models that have the smallest RMSE averaged over all locations and finally for each location the 50% of fully calibrated models (14 of 27) with the smallest RMSE for each particular location.

The relative grain yield change in Fig. 3a-d was calculated as:

$$r_k = \frac{\bar{y}_{future,k} - \bar{y}_{baseline,k}}{\bar{y}_{baseline,k}} * 100 \qquad (4)$$

The box and whisker plots show the distribution of responses from the wheat models. The vertical line in each box represents the median response, the box delimits the 25th to 75th percentiles, and the whiskers extend from the 10th to the 90th percentile.

Variation in model predictions of the effect of climate change in relation to calibration, soil and crop management (Fig. 2)

For Fig. 2, the 30-year base line climate assumes a CO_2 concentration of 360 ppm CO_2 (mean of 1995). The 30-year climate change scenario, an A2 emission scenario for 2070-2099 with 734 ppm CO2 at 2085, was drawn from the single GCM that best represented the seasonal temperature and precipitation changes from the wider ensemble of GCMs at the given location (Supplementary Table S3). This emission scenario (A2) and future time period (2070-2099) was selected as one with extreme expected changes in temperature and precipitation over the next 100 years for a sensitivity analysis. This ensured that the largest projected changes in climate are included in the model sensitivity analysis. The same local soil and crop management (except N and irrigation) was used for the baseline and sensitivity scenario. The crop management represents current practice at the selected locations, representative for the region of the location. Simulations were reset each year to the measured soil water and soil N contents from the field experiments before sowing to avoid carry-over effects. Dates for in-season crop management, N fertilizer (The Netherlands, India) and irrigation (India), were adjusted for phenology changes due to temperature changes in the sensitivity scenarios. An average application date was applied to each of the 30 years for each of the baseline, and sensitivity scenarios according to the mean temperature changes.

To analyze the impact of different soils, soil properties were manipulated by creating a +/-20%[65, 66] water-holding capacity at each location by changing the drained upper limit in each soil layer accordingly. To analyze the impact of different N-fertilizer management, N-fertilizer applications were varied by adjusting the N applications by +/-50% relative to the local crop management practice. To analyze the impact of sowing dates, the sowing dates were shifted 20 days earlier and 20 days later than the locally practiced sowing date.

Variation in model predictions (Fig. 3a-d)

The sensitivity analysis of Fig. 3 was carried out with 26 of the 27 wheat models (one modeling group was not able to carry out the sensitivity analysis), using the fully calibrated models. The relative yield changes are calculated as in eq. (4). The future weather scenarios use the baseline weather with temperature changes of -3°, 0°C, +3°C, +6°C or +9°C and CO_2 concentrations in 90 ppm increments from 360 ppm to 720 ppm (see Supplementary Table S4). Temperature changes were added to daily minimum and maximum temperature as used in the models. In addition to the scenarios presented in Fig. 2, scenarios with changes in N fertilization (Supplementary Table S4) and some specific combinations of changes in future climate and crop management (Supplementary Table S5) were tested.

Supplementary Table S4. Variable combinations altered in the sensitivity experiment[†]. All temperature by CO_2 combinations were simulated. +/-N was applied to all CO_2 changes, but not in combination with temperature.

Variable	Change				
Baseline weather with Temperature[‡]	-3°C	0° C	+3°C	+6°C	+9°C
Baseline weather with CO_2 concentration	360 ppm	450 ppm	540 ppm	630 ppm	720 ppm
Baseline weather with N[*]	100%	50%	150%		

[†] Carried out with 26 crop models (one modeling group was not able to participate in this analysis) for the four locations with 30 years. Changes were applied to 30-year baseline weather data (1981-2010).

[‡] Note, T_{max} and T_{min} were changed simultaneously for each day and all the temperatures are offsets from baseline temperature.

* Six crop models do not simulate N dynamics.

Supplementary Table S5. Climate-by-crop-management experiments[†].

Description
Baseline (360 ppm) + 7 days of T_{max}=35 ^{o}C start at measured anthesis date[x]
Baseline (360 ppm) - 20 days in sowing date
Baseline (360 ppm) + 20 days in sowing date
Baseline (360 ppm) - 20% PAW[‡] of soil
Baseline (360 ppm) + 20% PAW[‡] of soil
A2-End-of-Century scenario** 734 ppm - 20 days in sowing date
A2- End-of-Century scenario** 734 ppm + 20 days in sowing date
A2- End-of-Century scenario** 734 ppm 50% N fertilizer[*]
A2- End-of-Century scenario** 734 ppm 150% N fertilizer[*]
A2- End-of-Century scenario** 734 ppm - 20% PAW of soil
A2- End-of-Century scenario** 734 ppm + 20% PAW of soil

[†]Carried out with 26 crop models (one modeling group was not able to participate in this analysis) for the four locations with 30 years. Changes were applied to 30-year baseline weather data (1981-2010).

[x]Baseline temperatures were modified by including a maximum temperature of 35°C for 7 days starting at measured anthesis date for each location. If baseline temperatures exceeded 35°C, values were not adjusted.

[‡]PAW - Plant available water holding capacity of a soil. PAW was reduced or increased by 20% by changing the drain upper limit of the soil.

*Six models do not include N dynamics.

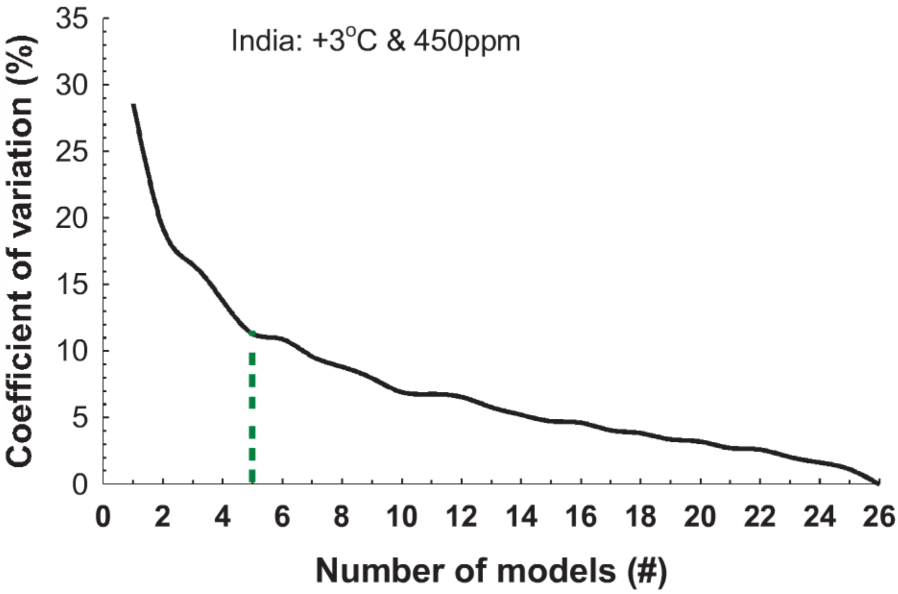
**Modified baseline climate series for each location according to GCM scenario listed in Table S3 to represent A2 End-of-Century (2070-2099) scenarios; 734 ppm CO_2 represents 2085 concentration from A2 scenario.

Observed impact of elevated CO_2 and temperature (Fig. 3e)

Fig. 3e in the main paper is based on the following data: Several FACE experiments in the USA, Germany and China have reported an 8 to 26 % grain yield increase with elevated atmospheric CO_2 concentrations of 550 ppm compared with 360 ppm[67-72]. Similarly, an average 3 to 10% wheat grain yield decline per 1^{o}C increase in mean temperature has been reported across several experiments[67, 73], though there is some evidence that the impact of temperature change on grain yield might be non-linear[74]. Acknowledging this, but for simplicity here, the reported impacts were linearly extrapolated in Fig. 3e to +3°C to allow for a general comparison with the simulation results in Fig. 3a-d.

Calculation of required number of models to reduce uncertainty (Fig. 4a)

Figure 4a is based on a sensitivity analysis with five temperature levels and five CO_2 concentrations at 100% N (Supplementary Table S4). We evaluated how variable the results would be if the number of models varied from m=1 to m=26 (one of the 27 models was not used in the sensitivity analysis). For each value of m, and for each site, we drew at random 260 combinations of model results (10 times the number of models, each representing a model) and calculated CV%. A typical result is shown in Supplementary Figure S1 for one of the locations, India. Such analysis was carried out for each location. The smallest m such that CV% < 13.5% (which is the experimental variation reported by Taylor et al.[64]) is the number of models reported. The average value of m across the four study locations is presented in Fig. 4a.



Supplementary Figure | S1. Illustration of calculated coefficient of variation (CV%) of simulated yield responses to a combination of temperature and CO_2 changes (+3 °C and 450 ppm) as a function of the number of average model responses randomly selected 260 times from the model results (calibrated models) for India. Vertical green line indicates number of models chosen in this case, i.e. the smallest number of models below the 13.5 CV% after Taylor et al.[64].

Comparing uncertainties of crop and General Circulation Models (Fig. 4b)

A scenario representing a A2 emission scenario for the 2040-2069 period (also referred to as 2050s, Mid- Century, 556 ppm of CO_2) from the ensemble of 16 General Circulation Models (GCM) (Supplementary Table S6) was used by 26 wheat models (one modeling group was not able to carry out this analysis). 30-year mean climatologies from each GCM were calculated for each month and the Mid-Century grid boxes corresponding to the four experimental locations were compared to the same grid box in the baseline period (1980-2009). The resulting monthly changes (aggregated to growing season means in Supplementary Table S7, but applied here on a monthly basis) were then imposed on the observed 30-year daily baseline climate series baselines following the so-called "delta change approach"[75].

Each crop model simulated each of the 16 GCM scenarios. The 30-year mean absolute impacts of the scenarios were calculated (30-year scenario mean minus 30-year baseline mean). Standard deviations were calculated for the absolute yield impacts separately across crop models and across the GCM's by using the model results from the 10th percentile to the 90th percentile of simulations based on multi-models (i.e. considering the 0-10th and 90-100th percentiles as outliers, consistent with the whisker plots used here). Standard deviations were used to calculate the coefficients of variation (CV%, equation 3) by using the observed grain yields from each location (supplied in Figure 4b) as basis for the calculation of CV to be directly comparable with observed data shown in Figure 1.

Supplementary Table S6: Sixteen General Circulation Models (GCM) models from CMIP3 General Circulation Models analyzed[76] used for climate changes scenarios.

GCM scenario	GCM	GCM source
A	bccr_bcm2.0	Bjerknes Centre for Climate Research, Norway
B	cccma_cgcm3.1(T63)	Canadian Centre for Climate Modeling and Analysis, Canada
C	cnrm_cm3	CERFACS, Center National Weather Research , METEO-FRANCE, France

D	csiro_mk3.0	CSIRO Atmospheric Research, Australia
E	gfdl_cm2.0	Geophysical Fluid Dynamics Laboratory, USA
F	gfdl_cm2.1	Geophysical Fluid Dynamics Laboratory, USA
G	giss_modelE_r	NASA Goddard Institute for Space Studies, USA
H	Inmcm3.0	Institute for Numerical Mathematics, Russia
I	ipsl_cm4	Institute Pierre Simon Laplace, France
J	miroc3.2 (medium resolution)	Center for Climate System Research; National Institute for Environmental Studies; Frontier Research Center for Global Change, Japan
K	miub_echo_g	Meteorological Institute of the University of Bonn, Germany
L	mpi_echam5	Max Planck Institute for Meteorology, Germany
M	mri_cgcm2.3.2a	Meteorological Research Institute, Japan
N	ncar_ccsm3.0	National Center for Atmospheric Research, USA
O	ncar_pcm1	National Center for Atmospheric Research, USA
P	ukmo_hadcm3	Hadley Centre for Climate Prediction, Met Office, UK

Supplementary Table S7: Projected change in mean growing-season temperature and percentage change in mean growing-season precipitation at each location for A2-2040-2069 (Mid- Century) scenarios from 16 GCMs.

Location	**Wageningen**	**Balcarce**	**New Delhi**	**Wongan Hills**
Country	**The Netherlands**	**Argentina**	**India**	**Australia**
GCM scenario	Change in mean growing season† temperature (^oC)			
A	1.56	1.26	1.58	1.24
B	1.39	1.01	2.63	1.85
C	1.67	1.29	2.12	1.56
D	1.33	1.01	1.62	1.51
E	1.52	1.27	3.00	1.55

F	1.12	1.01	2.22	1.50
G	1.84	0.84	2.13	1.88
H	1.44	1.37	2.95	1.34
I	2.14	1.33	2.42	1.84
J	1.96	1.33	2.17	1.51
K	1.20	1.13	1.73	1.53
L	1.46	0.77	2.20	1.54
M	1.28	1.19	1.65	1.30
N	1.96	1.33	2.22	2.23
O	1.06	1.00	1.53	1.03
P	1.22	1.60	2.42	1.84

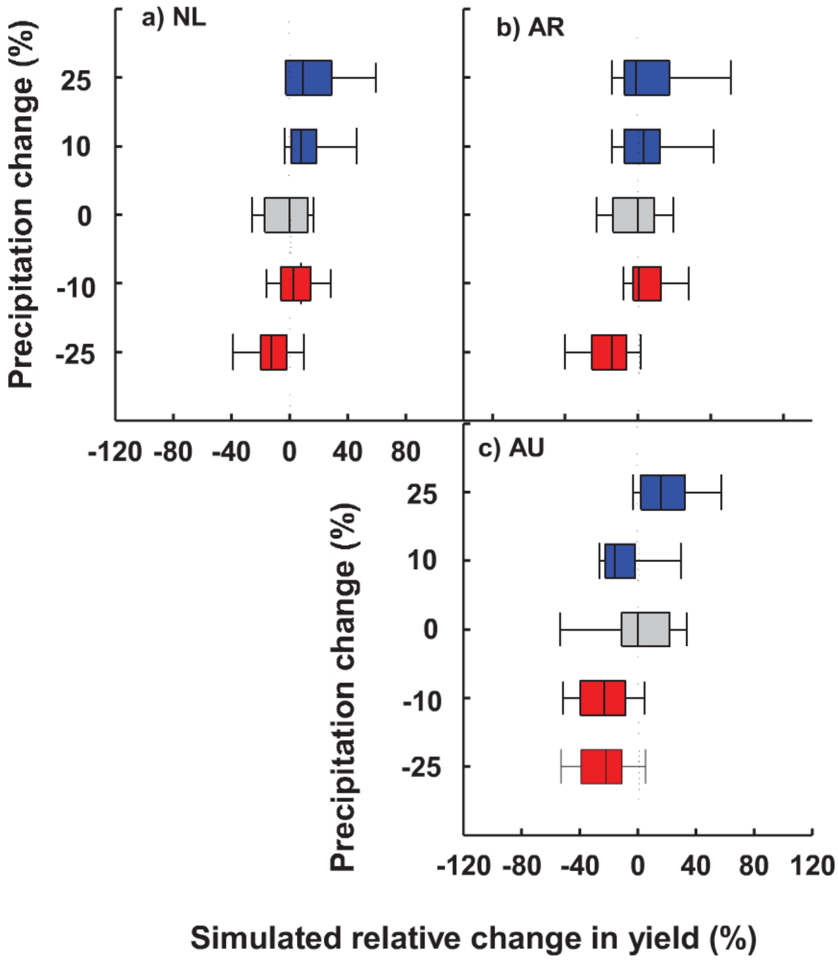
GCM scenario	Change in mean growing season[†] precipitation (%)			
A	8.7	10.4	-18.7	-14.1
B	6.3	0.4	-9.1	-23.3
C	2.3	1.7	-31.3	-21.5
D	16.8	12.4	6.5	-24.5
E	1.8	-8.3	-40.1	-29.2
F	2.2	-7.2	46.2	-24.2
G	-1.1	2.1	-2.3	-15.5
H	12.2	0.9	10.4	-19.1
I	-7.8	-14.3	-0.2	-21.4
J	2.5	-2.4	-6.7	-8.8
K	6.5	-5.1	27.7	-19.0
L	-1.4	-3.5	13.7	-22.8
M	4.4	-2.8	57.2	5.9
N	0.9	-4.9	12.0	-7.5
O	4.6	-0.7	-12.2	-12.9
P	-3.8	3.3	68.1	15.6

[†]Current growing season length. See Supplementary Table S3 for location specific growing season periods.

Supplementary Results

Precipitation impact

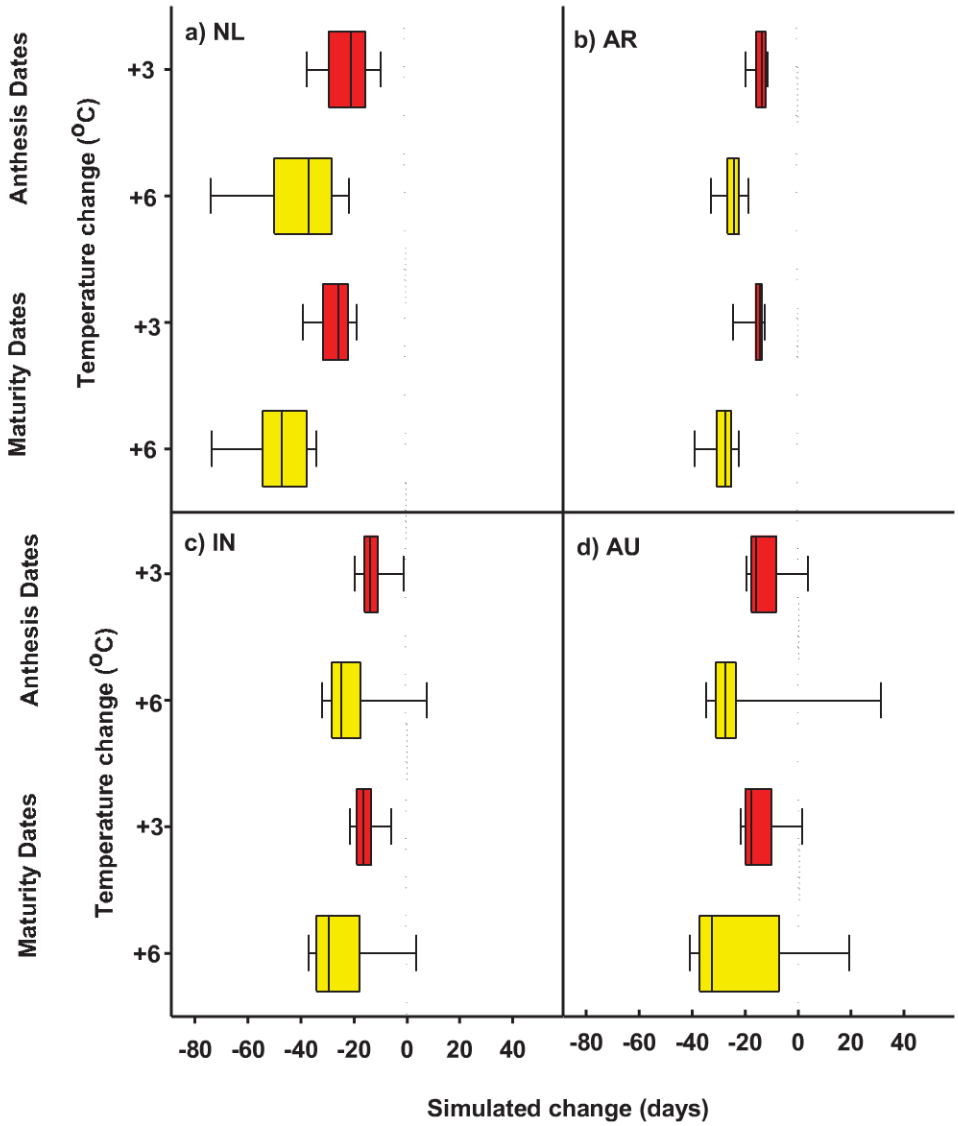
The simulated 30-year baseline yields were used to analyze the impact of growing-season precipitation changes on simulated yields. After sorting years according to mean seasonal temperature, yields from the mid-temperature tercile of the 30-year baselines for each location (except India which received irrigation) were selected to minimize a temperature effect, and compared with the yield from the year with the mean precipitation of this tercile. Years with about +10 and +25% higher growing-season precipitation and years with -10 and -25% less growing-season precipitation than the median of the mid-tercile were selected to calculate yield impacts from precipitation differences (i.e. difference in yield from year with +10, +25% higher precipitation, -10 and -25% less growing-season precipitation and the yield of the median precipitation year of the mid-temperature tercile. Growing-season precipitation differences had an impact on simulated yield but showed little impact on the variation in simulated yield change due to precipitation changes (Supplementary Fig. S2).



Supplementary Fig. S2. Simulated relative grain yield difference (change) for an increase (+10 and +25%) and a decrease (-10, -25%) in growing-season precipitation for the rain-fed sites a) The Netherlands (NL), b) Argentina (AR) and c) Australia (AU). For each box plot, vertical lines represent, from left to right, the 10th percentile, 25th percentile, median, 75th percentile and 90th percentile of simulations based on multi-models.

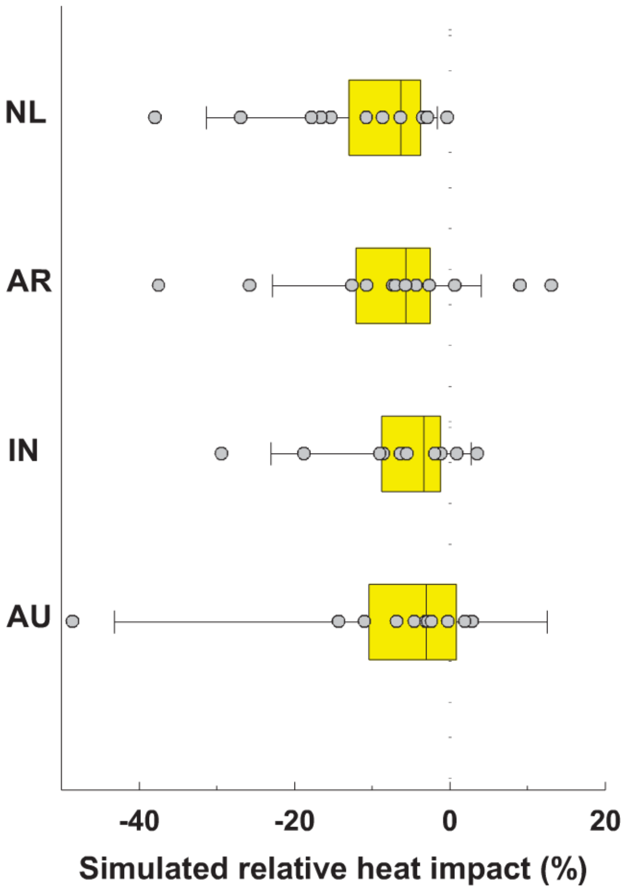
High temperature impact

Increased temperatures had an impact on simulated anthesis and maturity dates (Supplementary Fig. S3), which in turn affect simulated growth and grain yields.



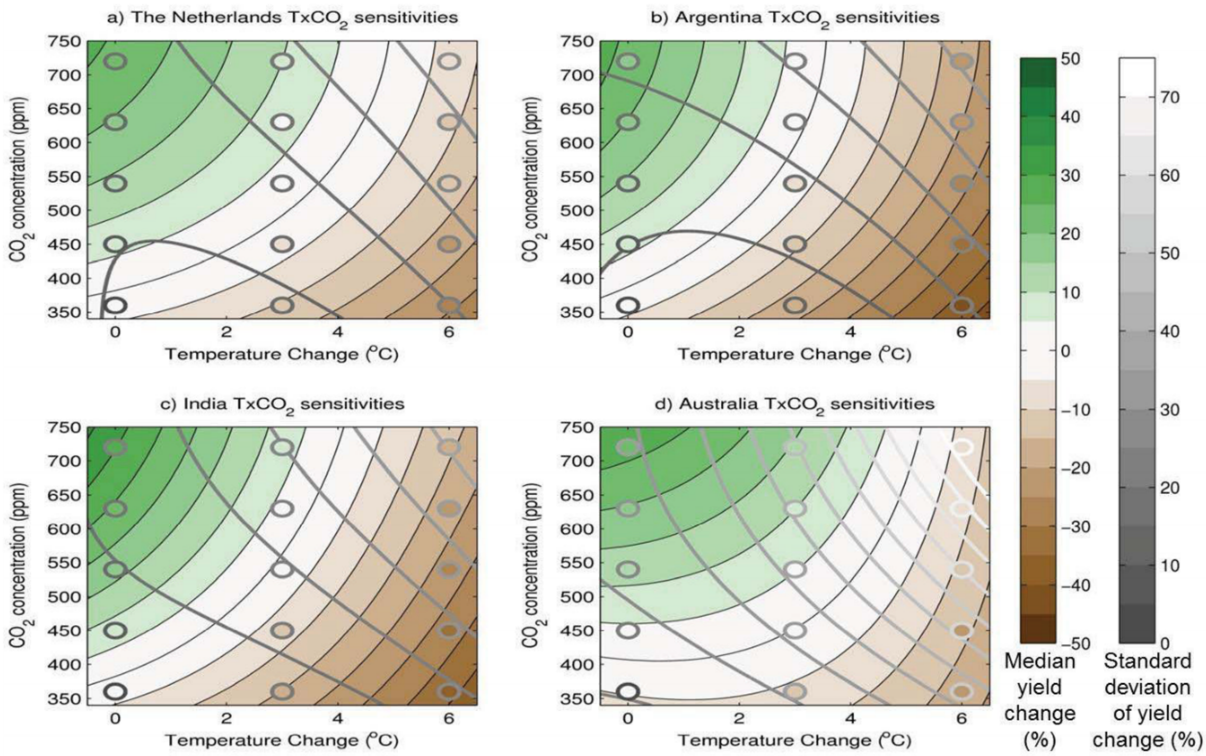
Supplementary Fig. S3. Simulated changes in anthesis and maturity dates with increased temperatures of +3°C (red) and +6°C (yellow). For each box plot, vertical lines represent, from left to right, the 10th percentile, 25th percentile, median, 75th percentile and 90th percentile of simulations based on multi-models.

The scenario with seven consecutive days of T_{max} of 35 °C at the mean anthesis date for each location is one of the special simulation experiments (Supplementary Table S5). The impact of this scenario is shown in Supplementary Fig. S4, indicating that some of the increased variation with increasing temperature in Fig. 3 is due to the contribution of variation in modeling heat stress impact on yields (Supplementary Fig. S4).



Supplementary Fig. S4. Simulated yield change from seven days of introduced T_{max} of 35 °C at the mean anthesis date for each location. For each box plot, vertical lines represent, from left to right, the 10th percentile, 25th percentile, median, 75th percentile and 90th percentile of simulations based on multi-models. Symbols indicate results from models which account for heat stress impact (see Supplementary Table S2, column 9)

Temperature by CO_2 impact



Supplementary Fig. S5: Response surfaces of crop model ensemble to temperature and atmospheric CO_2 concentration sensitivity tests at *a)* the Netherlands, *b)* Argentina, *c)* India, and *d)* Australia. The filled colours represent the median (across the 26 crop models) 30-year mean yield change (as a percentage of the mean 30-year yield for the 1981-2010 baseline period) for each of the sensitivity experiments (dots) as well as an emulated surface fit to these dots. The gray colours represent the standard deviation (across the 26 crop models) of the 30-year mean yield change (percentage of the 30-year mean baseline yield), with the outlines of the dots representing the experiments and the contours representing an emulated surface fit to these experimental standard deviations.

Response emulators for median yield change and the standard deviation of yield change (across the 26 crop models) were fit assuming a quadratic form (Supplementary Fig. S5):

$$E(T,[CO_2]) = a + bT + cT^2 + d[CO_2] + e[CO_2]^2 + fT[CO_2] + g\,(T[CO2])^2$$

where $E(T,CO_2)$ is the emulated response at a given temperature change T and CO_2 concentration ($[CO_2]$) and parameters *a-g* are fit using a least-squares fit.

The results indicate that the general pattern of yield sensitivities and their uncertainties is consistent from region to region, although the magnitude of the sensitivities varies from site to site. Yields tend to be decreased at higher temperature and increased at higher CO_2 concentration; however, at high temperatures the CO_2 benefits are reduced (Supplementary Fig. S5). As the ensemble of crop models is tested with climates that are increasingly dissimilar from the baseline period (e.g. very hot and with high CO_2), uncertainty also increases. This effect is strongest in Australia (where the baseline climate is hot and dry) and weakest in The Netherlands (where the baseline climate is cool and wet).

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