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# Title: Similar estimates of temperature impacts on global wheat yield by three independent methods

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Global warming, wheat yield, climate impacts, impact method comparison, food security, temperature

## Abstract

The potential impact of global temperature change on global crop yield has recently been assessed with different methods. Here we show that grid-based and point-based simulations and statistical regressions (from historic records), without deliberate adaptation or $CO_2$ fertilization effects, produce similar estimates of temperature impact on wheat yields at global and national scales. With a 1℃ global temperature increase, global wheat yield is projected to decline between 4.1% and 6.4%. Projected relative temperature impacts from different methods were similar for major wheat producing countries China, India, USA and France, but less so for Russia. Point-based and grid-based simulations, and to some extent the statistical regressions, were consistent in projecting that warmer regions are likely to suffer more yield loss with increasing temperature than cooler regions. By forming a multi-method ensemble, it was possible to quantify 'method uncertainty' in addition to model uncertainty. This significantly improves confidence in estimates of climate impacts on global food security.

126 Global demand for food is expected to increase 60% by the middle of the 21st century [1].
127 Climate change, and in particular rising temperatures, will impact food production [2]. For
128 global food security, it is important to understand how climate change will impact crop
129 production at the global scale to develop fact-based mitigation and adaptation strategies.
130 Many studies have shown a wide range of temperature impacts on yields of different crops in
131 different seasons at different locations [3], including Europe [4], China [5], India [6] and Sub-Saharan
132 Africa [7]. A few studies have considered impacts on the entire globe[8, 9, 10, 11]. However, the
133 methods used to make these assessments are based on very different premises and use
134 different methodological steps.
135 The uncertainty of estimates of global temperature impact on crop yields was analyzed
136 for the crop model component (i.e. model uncertainty) by using two different multi-model
137 ensemble approaches [8, 9]. While both studies used process-based crop simulation models, the
138 scaling approach and input data differed greatly. The first study divided the globe into a
139 geographical grid cells defined by latitude and longitude and used climate and crop
140 management data integrated over each grid as input for seven crop models [9]. This grid-based
141 system was used to estimate relative yield changes for rice, maize, wheat and soybean. The
142 second study used data from 30 individual field sites deemed to represent 2/3 of
143 wheat-producing areas worldwide [8]. In this point-based approach estimates from sentinel sites
144 were scaled up and extrapolated to cover geographical areas with similar conditions.
145 In further contrast, statistical regressions based on global and country level data have
146 been used to quantify the impact of increasing temperatures on yields of wheat, maize, barley,
147 soybean, sorghum and rice [10, 11]. An important difference from the simulation models is that

148 statistical models do not directly consider processes inherent to crop growth. However,
149 statistical models may include indirect effects of climatic variability, such as those related to
150 pests and diseases, which are not well captured by simulation models [12]. When assessing
151 climate effects on crop yields, crop models can take into account autonomous adaptation and
152 an increase in atmospheric $CO_2$ concentration. Also some statistical regressions include the
153 yield effects associated with autonomous adaptation [10]. For the effects of gradual increase in
154 $CO_2$ concentration in the past, statistical models may inherently include these within yield
155 effects [13], but for some regression models with a linear time term, effects of steady increase in
156 $CO_2$ can be removed from yield impacts, just as the effects of technology improvement. In
157 addition, upscaling methods influence the outcomes from regional assessments [14]. The
158 statistical approach obtained global or regional impacts by aggregating county districts or
159 countries [10, 11]. The grid-based system obtained global or regional impacts by aggregating $0.5^{o}$
160 $\times$ $0.5^{o}$ grid cells [9], while the point-based approach employed 30 sites to represent global wheat
161 regions [8]. Therefore, differences in upscaling could add uncertainties in the impact estimated
162 in these studies.

163 In this letter, we compared three largely independent assessment methods used to
164 estimate temperature impacts on wheat yields: grid-based simulations, point-based
165 simulations, and statistical regressions. The details of each method are shown in Table S1.
166 The methods used independent different dynamic, statistical, up-scaling and source data
167 approaches. The grid-based simulations used here were from the Agricultural Model
168 Intercomparison and Improvement Project (AgMIP) [15] as part of the Inter-Sectoral Impact
169 Model Intercomparison Project (ISI-MIP). Wheat yields were simulated with seven global

gridded crop models during 1980-2099 under RCP 8.5, a greenhouse gas emissions scenario (here without $CO_2$ fertilization effects), over $0.5^o \times 0.5^o$ grid cells [9]. The point-based simulations from the AgMIP-Wheat project [8] consisted of simulations from 30 wheat models (including one statistical model) for 30 representative locations around the world from a baseline of the 1981-2010 period and a linear temperature increase. Temperature impacts determined by statistical regression methods were obtained directly from previously published data or our own statistical analysis (Table S1 and Supplementary methods).

**Similar global impact from different methods**

The average reductions in global wheat yield with $1^oC$ global temperature increase estimated from grid-based simulations, point-based simulations, and statistical regressions at global level were all between 4.1% and 6.4% (Fig. 1). The average estimated temperature impact from all three methods (and four studies) was a 5.7% reduction in global yield per degree of global temperature increase. The estimated temperature effects on global wheat yield from the three different methods were similar.

A meta-analyses of mostly process-based crop model simulations, reported a 3.3 ± 0.8% decline in wheat yields with a $1^oC$ increase in local temperature [16]. When adjusted to global temperature change (which is usually less than local wheat region temperature changes [17]), this impact amounts to respectively 3.9% yield reduction per degree of global temperature increase. Also, a summary of past regression and simulation studies reported an average of 5.9% wheat yield decrease with $1^oC$ warming [18]. These values are very similar to the results obtained here for wheat using three different assessment methods.

The results here are presented for 1°C of global warming for consistency. However, the

192 estimated impacts do not increase linearly with increasing temperature and the disagreement
193 among method estimates become larger with more temperature change (Fig. S9).

194 **Impacts for major wheat-producing countries**

195 To understand how the different methods project such similar temperature impacts on
196 global wheat yields, we disaggregated the temperature impacts to the national scale.
197 Point-based and grid-based simulations were compared for 97 countries (Fig. 2a). Generally,
198 projected temperature impacts on wheat yields for most of the large wheat producers were
199 similar between the two simulation methods (with a $R^2$ of 0.64 for the top 20 producers,
200 Fig.S12), while differences were larger for small wheat-producing countries. Some large
201 differences occurred between point-based and grid-based simulation in irrigated semiarid
202 regions of Africa, which are mostly small wheat producers. The larger differences observed
203 for smaller producers have little weight in the global analysis. However, they are important
204 for regional economies. Method results were compared in more detail for the top five wheat
205 producing countries (Fig. 2b, Fig. 3). For China, India, USA, and France, the different
206 assessment methods resulted in similar values for temperature impacts on country wheat
207 yields. Additional country-level studies relying on other methods and data sources gave
208 similar estimates. For example, for China point-based simulations, grid-based simulations,
209 and two different regressions all concluded that yield reductions of about 3.0% are expected
210 with 1$^{o}$C warming (Fig.3a). For India, country-level statistical regressions, grid-based and
211 point-based simulations all estimated about 8.0% yield declines per °C of global temperature
212 increase (Fig.3b). For Russia, the two simulation methods agreed well, but yield reductions
213 estimated from statistical regression were markedly higher (Fig. 3c). Another study using

214 statistical regression methods also showed higher negative temperature impacts on wheat
215 yield than the two modeling methods used here for Rostov, a main wheat producing region in
216 Russia [19]. Since wheat producing regions in Russia can experience relatively low
217 temperatures (below optimal growth temperature) during early growing stages, a temperature
218 increase during this stage (tillering), may have a positive yield impact, while at a later stage
219 (booting or grain filling) an increase in temperature often reduces wheat yields [19]. As an
220 average temperature over a growing season is usually used in statistical regressions, such
221 in-season variability in temperature impacts would remain undetected. A dynamic crop
222 simulation model takes in-season variability and impacts into account. This may explain the
223 estimated larger impacts in Regression_A in comparison to the simulation results. For USA, a
224 recent study using data from wheat variety trials from 1985–2013 in Kansas, USA reported a
225 7.3% decrease (corrected for global temperature change) in wheat yield with 1$^{o}$C global
226 temperature increase[20]. This result is similar to the other estimated temperature impacts on
227 wheat yields for the USA (Fig. 3d). For France, yield reduction estimates from grid-based
228 simulations, point-based simulations, and statistical regressions were 4.6%, 5.2%, and 4.2%,
229 respectively (Fig. 3e). In an independent study, a 0.42t.ha$^{-1}$ reduction in wheat yields, which is
230 a reduction of about 5.5% after correction for global temperature change, was reported in
231 Northern France from 1998-2008 that included the planting of reference varieties in field
232 experiments [21]. This is also in line with simulated impact response surfaces from a
233 26-wheat-model-ensemble across a European transect[22].
234 With the different temperature impact methods used, despite some variation, there is a
235 general similarity in the magnitude of negative effects of increasing temperature on wheat

yields for major wheat producing countries. As the five largest wheat producing countries have a combined total >50% of total global wheat production [23], the similarity in method estimates of temperature impacts for these countries also dominates the similar negative temperature impacts computed at the global scale.

**Differences in model inputs**

At the location scale, the yields from the point-based simulations were highly correlated to the yields from the grid-based simulations for the baseline and baseline+1$^{o}$C periods ($P <$ 0.001, $R^2 > 0.5$; Table S2), but simulated yields were generally higher in point-based than in grid-based simulations (Fig. 4 and Fig. S1). The average yields of the 30 locations in the point-based simulations were 3.2 (82%) and 3.0 (82%) t.ha$^{-1}$ higher than in the corresponding grid-based simulations under baseline and baseline + 1$^{o}$C conditions, respectively. In both studies, mean temperatures were similar across sites for the 90 days period prior to maturity, except for three locations (Fig. S2). Seasonal temperature variability in the model input data differed slightly between methods and caused a larger seasonal yield variability in the grid-based simulations compared to the point-based simulations (Fig S7). Solar radiation inputs were 5% to 7% lower in the grid-based than in the point-based simulations (Fig. S3), which might have contributed slightly to the simulated yield difference [24]. Water stress was not considered in either study for the comparison of these 30 locations and any possible differences in precipitation inputs had no impact on the simulated results (Table S3). No nitrogen stress was assumed in the point-based simulations , but four of the seven crop models in the grid-based simulations did consider country-level average N fertilizer application which could explain why the grid-based model ensemble simulated generally

lower yields compared to the point-based simulations (Table S3).

Another important factor possibly contributing to yield differences between the grid-based and point-based simulation at the local scale were the models used in the studies. There were 29 crop models and one statistical regression in the point-based simulation ensemble, whereas there were seven crop models in the grid-based simulations. Three models (CERES, EPIC, and LPJmL) were common to both studies. These three models tended to simulate lower yields than the 30-model ensemble average from the point-based study for the 30 locations, e.g., about 0.9 $t \cdot ha^{-1}$ less in the baseline period (Fig. S4). This may have lowered the average simulated yields in grid-based simulations. Differences in the calibration of the crop models would also affect simulations[25]. Some models in the grid-based simulations were calibrated and some were not, and especially growing periods were not harmonized across grid-based models [9], while in point-based simulations all models were calibrated for anthesis and maturity dates with local phenology information [8]. Hence, differences in models, solar radiation and inputs like N fertilizer may explain some of the lower yields found in the grid-based studies. Differences in cultivar calibration, particularly for phenology and growing season, adds another source of differences between these two studies.

**More yield reduction at warmer regions**

Interestingly, when comparing the grid-based and point-based simulations, no obvious bias was observed in the simulated relative yield impacts between point-based and grid-based simulations (Fig. 4c and Fig.S1c), even though simulated absolute yields with point-based simulations were much higher than grid-based simulations. This was still true when the outlier location in Fig. 4c was removed from calculations. Temperature impacts at the local

scale in grid-based and point-based simulations were highly correlated. With 1°C global temperature increase, higher yield reductions were observed at locations with higher baseline temperatures than locations with lower baseline temperatures in both point-based and grid-based simulations (Fig. 4c). For example, at Aswan in Egypt, point-based and grid-based simulations showed about 11% and 20% decline in yield with 1°C temperature increase, while for Krasnodar in Russia, point-based and grid-based simulations estimated about 4% and 7% yield decline with 1°C global increase. The spatial pattern of temperature impacts at the location scale was also consistent with that at the country scale (Fig. 2a, Fig. 2b, and Fig.S11), which indicated that warmer regions (e.g. India) are likely to suffer more wheat yield reductions than cooler regions (e.g. China). The exception is for statistical regression estimates for Russia, a generally cooler region (Fig. 2b). The effects of temperature on wheat yields are consistent with reports of impacts on other crops, such as maize, soybean, and cotton[26, 27, 28]. An increase in extreme temperature events with increasing mean temperatures [29] are likely to further contribute to yield decline in wheat [30, 31]. Several crop models used in point-based simulations (tested against warming experiments) and Regression_A (using a nonlinear regression method), also considered the impacts of extreme temperature[8, 10].

**Effects of up-scaling methods**

To assess climate impacts on global or country-level crop production, both process-based crop modeling approaches and statistical regressions need to be upscaled from locations to regions and then to the entire globe [32]. In the point-based simulations, a range of local information (e.g. local sowing dates, cultivar, anthesis and maturity date) was used for the 30 locations selected to represent about 70% of current global wheat production, which was then

upscaled via FAO statistics [8]. Much less local information was available for each of the 0.5° × 0.5° grid cells which were aggregated to country and global scales in the grid-based simulations [9]. However, very similar estimated temperature impacts on relative global yield changes were simulated with both approaches. This was surprising as Ewert, van Bussel [14] showed that scaling methods can add significant uncertainties to simulated outcomes. Although uncertainties are known to be reduced with multi-model ensembles, these results might also indicate that the selected 30 locations in the point-based study [8] were indeed representative of agro-climatic variability of wheat growing conditions throughout the world. The results also suggest that global grid-based models, despite having limited local information, are on a par with point-based approaches, while providing greater coverage of regional heterogeneity.

In the statistical regression methods, yield and weather data from different scales were used to obtain global and country-level temperature impacts. For example, both global [11] and country [10] level regressions, observed yield records were used to conduct global assessments, and both country-level yields and county (or similar) level yields were used for country assessments (e.g. for China, India, and USA). Generally, regressions with different spatial scales resulted in similar temperature impacts on yields.

**Advantage of different assessment methods**

Compared with process-based crop models, statistical regressions are simpler and require less input information. However, other important growth factors which change with climate change, such as radiation or the combined effects of heat, water and nutrient stresses, vary over the period of a crop growing cycle, but are often not directly considered in statistical

regressions. Some of these factors might also be confounded in a statistical regression analysis. While there have been attempts to include more factors in statistical impact methods [33], detailed process-based, dynamic crop simulation models may be more suitable to simulate the more complex climate change scenarios, beyond the single impact of temperature change. However, process-based models, like statistical methods, often do not account for many other important factors required for holistic climate change impact assessment. Such factors include impacts from frost, pests, weeds, diseases, and floods, and also dissimilar impacts between day and night temperatures [34], or extreme temperature events at different growth stages, which are all likely to change with future climates. However, process-based models are capable of accounting for the effects of elevated $CO_2$ [35], even though this effect is not considered here, but large uncertainties exist not only with respect to the general effects on crop yields [36, 37] but also with respect to model implementation [9, 38].

Field or environment-controlled experiments are independent ways to estimate temperature impacts on wheat yields[8, 16]. For example, 2% to 8% reductions in wheat yield for every 1$^{o}$C increase of post-anthesis temperature above an optimum season-average temperature of 15$^{o}$C (i.e. local temperature) have been measured for a range of cultivars under controlled [39] and field experiments [40]. Considerable variations of wheat yield impacts with increasing temperature have been found in a 4-growing season warming experiments [41]. However, while measured temperature impacts on yields can guide other impact estimation methods, they are often specific to a particular location, cultivar, crop management or experimental treatment and are not representative of a larger region, which makes it difficult to extrapolate such measurements to regional or global impacts.

346 **Applying multi-method ensembles**

347 Understanding and quantifying uncertainty of impact assessments has been a key aspect
348 in assessing climate impacts on crop production in recent studies[25, 42, 43]. Most previous studies
349 have focused on uncertainties arising from crop models or climate models[25]. Here the
350 uncertainties in both point-based and grid-based simulations were quantified by multi-model
351 ensembles. Uncertainties due to crop models, expressed as error bars in the grid-based
352 simulations, were relatively large at both global and country scales (Fig. 1 & Fig. 3), which
353 was due to the limited number of models and relatively wide spread of model results in this
354 study. The differences in model inputs (e.g. nitrogen application, sowing dates, cultivars),
355 calibration methods and model [9] explain some of the variability between the point and
356 grid-based simulations. Many crop models do not simulate temperature interactions with
357 canopy temperature variation under different soil water conditions, which could result in
358 simulated differences of temperature impacts [8]. However, multi-model ensemble medians
359 have been shown to be more consistently accurate than individual models when comparing
360 measurements across locations and growing environments, adding confidence to the estimates
361 here[44]. Bootstrap resampling methods were employed to estimate the uncertainty of
362 temperature impacts calculated in the two global scale statistical regressions. Thus different
363 assessment approaches have independent methods of quantifying uncertainty. Multi-method
364 ensembles can enable the quantification of method uncertainty, similar to how multi-model
365 ensembles enable estimation of model uncertainty. The uncertainty range of wheat yield
366 reduction with 1$^{o}$C global temperature increase from the multi-method ensemble calculated
367 from the median of the four methods analyzed here was between 4.0% and 6.9% at the global

368 scale (95% confidence interval). While this absolute difference is still substantial, this is
369 narrower than the uncertainty due to the models in the multi-model ensembles from the
370 simulations or the boot-strapping method in the statistical regressions. Therefore, applying
371 multi-method ensembles can improve reliability of the assessment of climate impacts on
372 global food security.

373 However, the consistency of negative global yield impacts of increasing temperature
374 quantified here at global level should not be applied to local or regional scale. As previous
375 studies have found, there were considerable large variations of increasing temperature
376 impacts on wheat yields at local and regional scale[8, 45], and the spatial variation of temperature
377 impacts has also been observed in the two modeling approaches here among different
378 locations.

379 Adaptation to global warming, e.g. farmer's autonomous adaptation through changing
380 sowing dates or cultivars, has been suggested in several studies to compensate negative
381 impacts of increasing temperature [46]. At global scale, point-based simulations did not consider
382 adaptation. Also a panel regression approach attempted to exclude adaptations [10]. In the
383 grid-based simulations, four of the seven models did allow cultivar and sowing date
384 adaptation with a changing climate (Table S3), and the simulated impacts tended to be lower
385 with simulated adaptation (Fig.S10). However, temperature impacts from models with
386 adaptation varied largely. Temperature impacts with and without adaptation were estimated
387 from different models in grid-based simulations, which added considerable uncertainty in the
388 results. The adaptation effects on temperature impacts should be further studied with more
389 consistent protocols for multi-model assessments. Other future adaptation, e.g. wheat

cultivation shifting to marginal regions in higher latitudes, could offset some of the negative impacts.

Assessing climate change impacts on crop production is a key aspect in determining appropriate global food security strategies [42]. Reliable estimates of climate change impacts on food security require an integrated use of climate, crop, and economic models[15]. Applying multi-method ensembles further improves the estimated impact precision and confidence in assessments of climate impacts on global food security. The consistent negative impact from increasing temperatures confirmed by three independent methods warrants critical needed investment in climate change adaptation strategies to counteract the adverse effects of rising temperatures on global wheat production, including genetic improvement and management adjustments [47, 48]. However, some or all of the negative global warming impacts on wheat yield might be compensated by increasing atmospheric $CO_2$ concentrations under full irrigation and fertilization[25].

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## Author contributions

B.L., S.A., C.M., F.E., J.E., D.B.L., P.M., A.C.R., D.W., J.W.J., C.R. and Y.Z. motivated the study, S.A. coordinated the study, B.L. S.A., C.M., F.E., J.E., D.B.L., P.M., A.C.R., and D.W. analyzed data, P.K.A., P.D.A., J.A., B.B., C.B., D.C., A.J.C., D.D., G.D.S., J.D., E.F., C.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., T.A.M.P.,, E.E.R., R.R.P., E.S., M.A.S., I.S., E.S., C.O.S., P.S., T.S., I.S., 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, C.M., J.E., 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, B.L., S.A., C.M., F.E., J.E., D.B.L., P.M., A.C.R., D.W., J.W.J., C.R. and Y.Z. wrote the paper. All other authors gave comments on the earlier version of this manuscript.

## Competing financial interests

The authors declare no competing financial interests.

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## Figure legends

**Figure 1 | Impacts of 1°C global temperature increase on global wheat yield estimated by different assessment methods.** The grid-based (0.5° x 0.5° grid cells) method is an ensemble median from seven global gridded crop models, averaged over 30 years and aggregated over all simulated grid cells (after Ref. 9). The point-based method is an ensemble median from 30 models, averaged over 30 years and aggregated over 30 global locations (after Ref. 8). Regression_A is based on a country-level statistical regression from Ref. 10. Regression_B is based on a global level statistical regression from Ref.11. The error bars for four different methods indicate the 95% confidence intervals based on multi-model ensembles in the simulations and bootstrap resampling in the statistical regressions. The mean of the method_ensemble is shown with error bar indicating the 95% confidence intervals based on medians of individual methods.

**Figure 2 | Comparison of wheat yield changes with 1°C global temperature increase for 97 wheat producing countries estimated using three different methods.** (a) Median simulations of a grid-based (0.5° × 0.5°) ensemble of seven models (after Ref. 9) versus a point-based (30 locations over 30 years) ensemble of 30 models (after Ref. 8). (b) Country level statistical regression for China, India, USA, France and Russia, the top five wheat producing countries, from Ref. 10 versus point-based simulations for these countries (after Ref. 8). Note, only data on these five countries were supplied in Ref. 10. Circle color indicates the wheat growing season

temperature (from Ref. 10). Circle size indicates the amount of wheat production for each country according to FAO statistics [23]. The solid line is the 1:1 line and dashed lines represent 0% yield change.

**Figure 3 | Estimated impacts of 1°C global temperature increase on wheat yield** (a) China, (b) India, (c) Russia, (d) USA, and (e) France using different assessment methods. The grid-based ($0.5^o \times 0.5^o$) method produced an ensemble median from seven global gridded crop models (after Ref. 9). The point-based method produced an ensemble median from 30 models from 1 to 3 country locations (after Ref. 8). Regression_A is a statistical regression based on country statistics after Ref. 10. Regression_C is a statistical regression based on $0.5^o \times 0.5^o$ grid statistics after Ref. 45. Regression_D is county level statistical regressions produced by two different regression methods from Ref. 50. Regression_E is a county level regression produced for this study. The error bars indicate the 95% confidence interval based on multi-models for the simulations and bootstrap resampling (Regression_A, Regression_B, and Regression_D) or t-tests (Regression_E) for the statistical regressions. No error bar was provided for Regression_C in Ref. 45.

**Figure 4 | Comparison of simulated multi-model median wheat yield and yield changes.** Absolute wheat yields for (a) baseline and (b) baseline + 1°C periods, and (c) relative yield change with 1°C global temperature increase from grid-based simulations ($0.5^o$ x $0.5^o$) (from Ref. 9) of cells centered around the 30 locations from

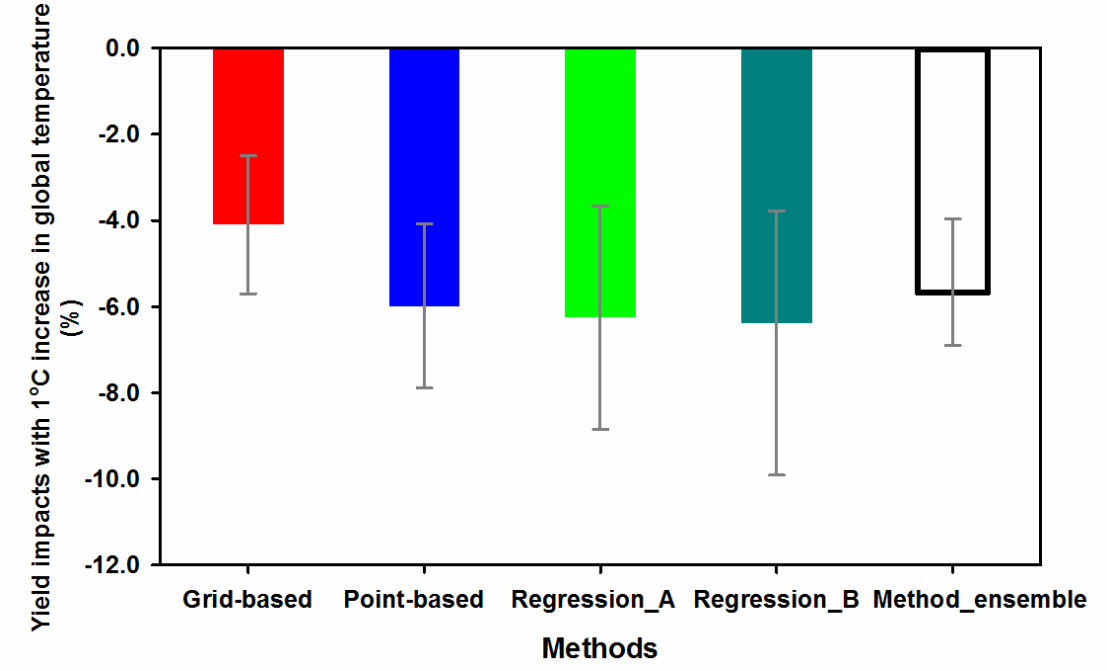
663 the point-based study versus that from the point-based simulations (from Ref. 8). Note

664 in (c), regression line is drawn without outlier (location in Sudan).

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667 **Figure 1.**

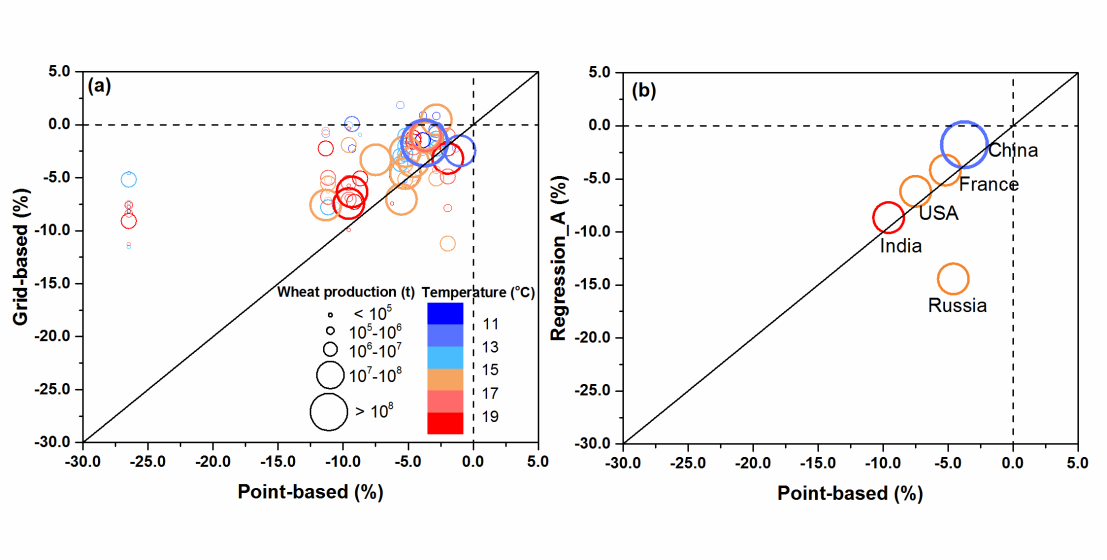



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671 **Figure 2.**

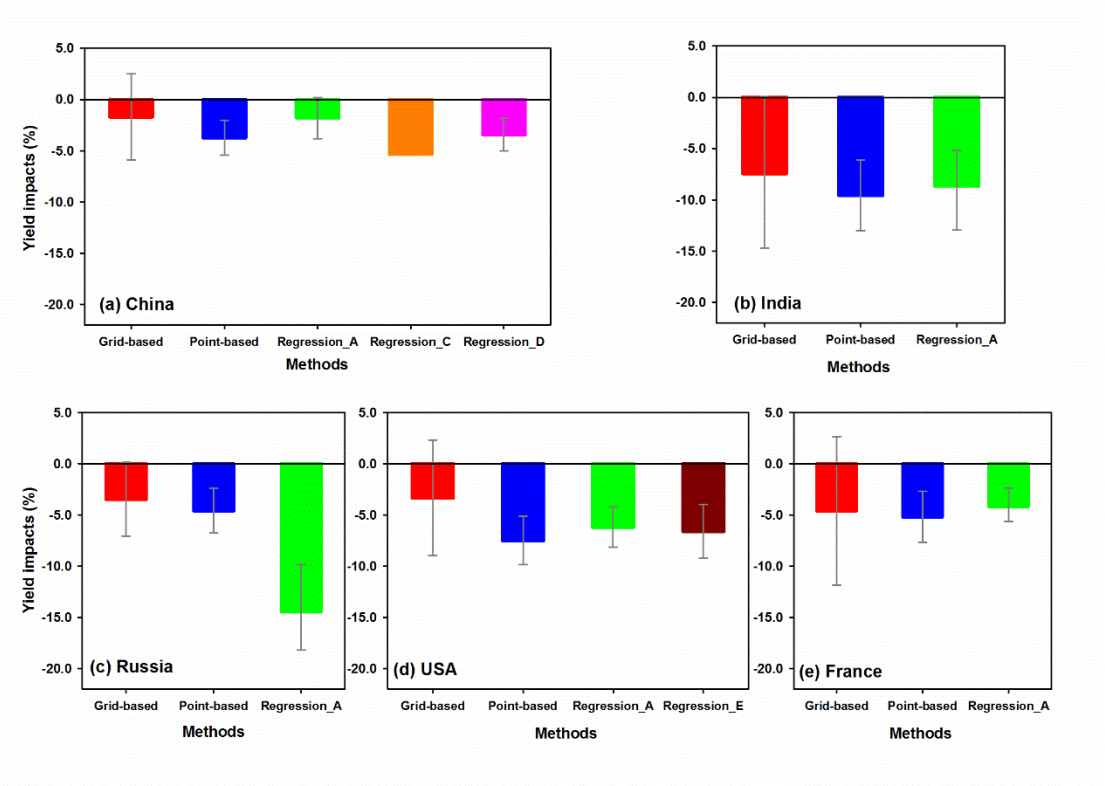



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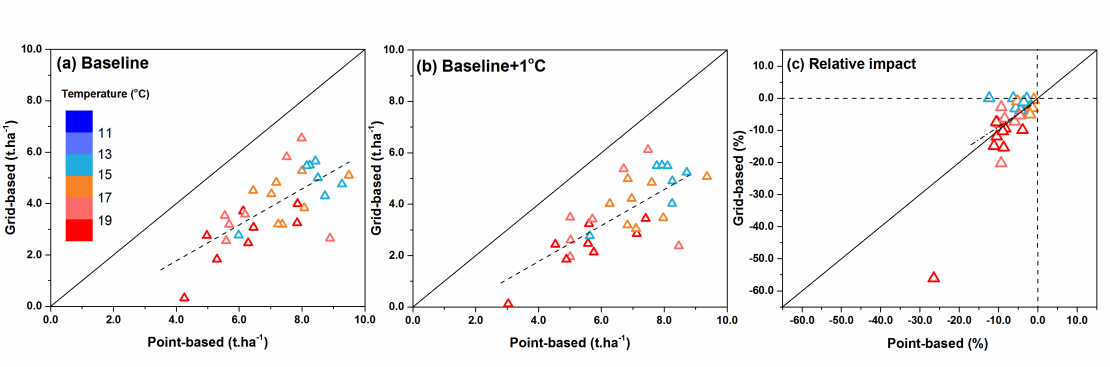
675 **Figure 3.**




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678 **Figure 4.**




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## Methods

*Grid-based simulations*. Seven global gridded models simulated $0.5^{o} \times 0.5^{o}$ grid cells across all wheat growing regions of the world from 1980 to 2099 under a RCP8.5 scenario with a statistically-downscaled version of HadGEM2-ES [49], with only a small trend in solar radiation at some locations (Fig. S6). Here, a set of simulation experiments without effects of elevated $CO_2$ and under full irrigation treatments were used. Among the seven global gridded models, adaptation through cultivars, sowing dates or growing season had been employed in four of the models (Table S3). The global yield impacts from models with and without adaptation are compared in Fig. S10. Only one climate model and RCP were used as there was limited data available for grid-based simulations. The period 2029-2058 was selected as being on average $2^{o}$C warmer globally than the baseline period of 1981-2010 and the impact was halved to adjust the temperature change to $+1^{o}$C for the analysis here. The temperature change considered here is $1^{o}$C warming of the global mean temperature, including land and ocean surface. The change in simulated grain yields between these two temperature periods was used to estimate temperature impacts on wheat at global and national scales. Grid-based simulations for the direct comparison to point-based simulations were extracted from simulations assuming full irrigation. For national and global scale results, grid-based simulations were aggregated by area-weighted means, using rain-fed and irrigated wheat areas per pixel of MIRCA2000 [50] combining simulations under irrigated and rain-fed conditions. To make projections between the different grid-based models comparable, yield simulations were bias-corrected to national FAO levels by using FAO mean yields and superimposing projected relative changes. More details about the grid-based simulations can

703 be found in Ref. 9.

704 *Point-based simulations*. Thirty models, 29 crop simulation models and one statistical
705 regression model, were used to simulate wheat grain yields for 30 representative locations in
706 high rainfall and irrigated wheat growing regions around the world (together representing
707 about 70% of global wheat production) with the estimated baseline period of 1981-2010 and
708 baseline + 2$^{o}$C. Three models (CERES, EPIC, and LPJmL) in point-based simulations were
709 used in grid-based simulations. No $CO_2$ fertilization effects or any adaptation was considered
710 in the point-based simulations. The impact was halved to adjust the temperature change to
711 +1$^{o}$C for the analysis here. Local temperature impacts on yields were adjusted to global
712 temperature change and upscaled via FAO statistics. Temperature impacts on national scales
713 were assessed for 125 countries. Each country was assigned as being similar to one or more
714 representative locations, so the temperature impacts of each country were the average impacts
715 of the corresponding representative locations. More details can be found in Ref. 8.

716 *Statistical regressions*. All estimated temperature impacts from statistical regressions were
717 from literature reports[10, 11, 45, 51], except for one new statistical regression analysis for the USA
718 that we present here (Supplementary Methods). All temperature impacts were adjusted to
719 global temperature change following the approach by Ref. 8. Details of these regression
720 studies and impacts adjustments are summarized in Table S1.

721 *Meta-analysis and experimental data*. Meta-analysis and experimental data from the literature
722 are cited here for further comparison after adjusting them to global temperature change where
723 possible. Meta-analysis and experimental data from the literature were cited here for further
724 comparison after adjusting them to global temperature change. An adjustment factor to global

725 temperature used for the statistical regressions was also used here. The temperature factors
726 are listed in Table S1.
727 *Comparison at a national scale.* Temperature impacts for 97 countries from both grid-based
728 and point-based simulations were compared. Due to the limited number of country-scale
729 estimates of temperature impacts on wheat yields with statistical regression analysis, we
730 compared the regression results with the two simulation approaches for the top five wheat
731 producing countries (Table S1).
732 *Comparison at local scales.* Yield simulations from 30 single grid cells from the grid-based
733 method were chosen that were centered around the 30 global representative locations from the
734 point-based method. Full irrigation treatments were applied in point-based and grid-based
735 simulations. The baseline and increased temperature periods for the 30 grid cells were
736 determined individually by matching the 30-year average annual temperature of each grid to
737 the 30-year average annual temperature of the corresponding location from point-based
738 simulations. The baseline and increased temperature periods for each of the 30 grid cells and
739 temperature differences between the two methods are shown in Table S4. Most locations had
740 very similar temperature input data in the two comparison periods for grid-based and
741 point-based simulations. Outliers (Table S4) were found where the input data differed
742 substantially but these did not cause outliers in yield impacts. The yield impact outlier at the
743 Sudan location was caused by very low simulated yields (Fig. 4). The simulated yields for
744 baseline and increased temperature periods were used to calculate temperature impacts at the
745 local scale. These were also adjusted to global temperature change with the same method at
746 global and national scales. The temperature and radiation data from the critical growing

747 period of wheat from 90 days before maturity to maturity were compared. Maturity dates

748 were the dates supplied from observations for each location in the point-based method [8].

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