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2 **Title: Similar estimates of temperature impacts on global wheat yield by three**
3 **independent methods**

4
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107 **Keywords:**

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

110

111 **Abstract**

112 The potential impact of global temperature change on global crop yield has recently been
113 assessed with different methods. Here we show that grid-based and point-based simulations
114 and statistical regressions (from historic records), without deliberate adaptation or CO₂
115 fertilization effects, produce similar estimates of temperature impact on wheat yields at global
116 and national scales. With a 1 °C global temperature increase, global wheat yield is projected
117 to decline between 4.1% and 6.4%. Projected relative temperature impacts from different
118 methods were similar for major wheat producing countries China, India, USA and France, but
119 less so for Russia. Point-based and grid-based simulations, and to some extent the statistical
120 regressions, were consistent in projecting that warmer regions are likely to suffer more yield
121 loss with increasing temperature than cooler regions. By forming a multi-method ensemble, it
122 was possible to quantify 'method uncertainty' in addition to model uncertainty. This
123 significantly improves confidence in estimates of climate impacts on global food security.

124 Global demand for food is expected to increase 60% by the middle of the 21st century ¹.
125 Climate change, and in particular rising temperatures, will impact food production ². For
126 global food security, it is important to understand how climate change will impact crop
127 production at the global scale to develop fact-based mitigation and adaptation strategies.
128 Many studies have shown a wide range of temperature impacts on yields of different crops in
129 different seasons at different locations ³, including Europe ⁴, China ⁵, India ⁶ and Sub-Saharan
130 Africa ⁷. A few studies have considered impacts on the entire globe^{8,9,10,11}. However, the
131 methods used to make these assessments are based on very different premises and use
132 different methodological steps.

133 The uncertainty of estimates of global temperature impact on crop yields was analyzed
134 for the crop model component (i.e. model uncertainty) by using two different multi-model
135 ensemble approaches ^{8,9}. While both studies used process-based crop simulation models, the
136 scaling approach and input data differed greatly. The first study divided the globe into a
137 geographical grid cells defined by latitude and longitude and used climate and crop
138 management data integrated over each grid as input for seven crop models ⁹. This grid-based
139 system was used to estimate relative yield changes for rice, maize, wheat and soybean. The
140 second study used data from 30 individual field sites deemed to represent 2/3 of
141 wheat-producing areas worldwide ⁸. In this point-based approach estimates from sentinel sites
142 were scaled up and extrapolated to cover geographical areas with similar conditions.

143 In further contrast, statistical regressions based on global and country level data have
144 been used to quantify the impact of increasing temperatures on yields of wheat, maize, barley,
145 soybean, sorghum and rice ^{10,11}. An important difference from the simulation models is that

146 statistical models do not directly consider processes inherent to crop growth. However,
147 statistical models may include indirect effects of climatic variability, such as those related to
148 pests and diseases, which are not well captured by simulation models ¹². When assessing
149 climate effects on crop yields, crop models can take into account autonomous adaptation and
150 an increase in atmospheric CO₂ concentration. Also some statistical regressions include the
151 yield effects associated with autonomous adaptation ¹⁰. For the effects of gradual increase in
152 CO₂ concentration in the past, statistical models may inherently include these within yield
153 effects ¹³, but for some regression models with a linear time term, effects of steady increase in
154 CO₂ can be removed from yield impacts, just as the effects of technology improvement. In
155 addition, upscaling methods influence the outcomes from regional assessments ¹⁴. The
156 statistical approach obtained global or regional impacts by aggregating county districts or
157 countries ^{10, 11}. The grid-based system obtained global or regional impacts by aggregating 0.5°
158 × 0.5° grid cells ⁹, while the point-based approach employed 30 sites to represent global wheat
159 regions ⁸. Therefore, differences in upscaling could add uncertainties in the impact estimated
160 in these studies.

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

168 gridded crop models during 1980-2099 under RCP 8.5, a greenhouse gas emissions scenario
169 (here without CO₂ fertilization effects), over 0.5° × 0.5° grid cells⁹. The point-based
170 simulations from the AgMIP-Wheat project⁸ consisted of simulations from 30 wheat models
171 (including one statistical model) for 30 representative locations around the world from a
172 baseline of the 1981-2010 period and a linear temperature increase. Temperature impacts
173 determined by statistical regression methods were obtained directly from previously
174 published data or our own statistical analysis (Table S1 and Supplementary methods).

175 **Similar global impact from different methods**

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

182 A meta-analysis of mostly process-based crop model simulations, reported a $3.3 \pm 0.8\%$
183 decline in wheat yields with a 1°C increase in local temperature¹⁶. When adjusted to global
184 temperature change (which is usually less than local wheat region temperature changes¹⁷),
185 this impact amounts to respectively 3.9% yield reduction per degree of global temperature
186 increase. Also, a summary of past regression and simulation studies reported an average of 5.9%
187 wheat yield decrease with 1°C warming¹⁸. These values are very similar to the results
188 obtained here for wheat using three different assessment methods.

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

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

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

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

212 statistical regression methods also showed higher negative temperature impacts on wheat
213 yield than the two modeling methods used here for Rostov, a main wheat producing region in
214 Russia¹⁹. Since wheat producing regions in Russia can experience relatively low
215 temperatures (below optimal growth temperature) during early growing stages, a temperature
216 increase during this stage (tillering), may have a positive yield impact, while at a later stage
217 (booting or grain filling) an increase in temperature often reduces wheat yields¹⁹. As an
218 average temperature over a growing season is usually used in statistical regressions, such
219 in-season variability in temperature impacts would remain undetected. A dynamic crop
220 simulation model takes in-season variability and impacts into account. This may explain the
221 estimated larger impacts in Regression_A in comparison to the simulation results. For USA, a
222 recent study using data from wheat variety trials from 1985–2013 in Kansas, USA reported a
223 7.3% decrease (corrected for global temperature change) in wheat yield with 1°C global
224 temperature increase²⁰. This result is similar to the other estimated temperature impacts on
225 wheat yields for the USA (Fig. 3d). For France, yield reduction estimates from grid-based
226 simulations, point-based simulations, and statistical regressions were 4.6%, 5.2%, and 4.2%,
227 respectively (Fig. 3e). In an independent study, a 0.42t.ha⁻¹ reduction in wheat yields, which is
228 a reduction of about 5.5% after correction for global temperature change, was reported in
229 Northern France from 1998-2008 that included the planting of reference varieties in field
230 experiments²¹. This is also in line with simulated impact response surfaces from a
231 26-wheat-model-ensemble across a European transect²².

232 With the different temperature impact methods used, despite some variation, there is a
233 general similarity in the magnitude of negative effects of increasing temperature on wheat

234 yields for major wheat producing countries. As the five largest wheat producing countries
235 have a combined total >50% of total global wheat production²³, the similarity in method
236 estimates of temperature impacts for these countries also dominates the similar negative
237 temperature impacts computed at the global scale.

238 **Differences in model inputs**

239 At the location scale, the yields from the point-based simulations were highly correlated
240 to the yields from the grid-based simulations for the baseline and baseline+1°C periods ($P <$
241 0.001 , $R^2 > 0.5$; Table S2), but simulated yields were generally higher in point-based than in
242 grid-based simulations (Fig. 4 and Fig. S1). The average yields of the 30 locations in the
243 point-based simulations were 3.2 (82%) and 3.0 (82%) t.ha⁻¹ higher than in the corresponding
244 grid-based simulations under baseline and baseline + 1°C conditions, respectively. In both
245 studies, mean temperatures were similar across sites for the 90 days period prior to maturity,
246 except for three locations (Fig. S2). Seasonal temperature variability in the model input data
247 differed slightly between methods and caused a larger seasonal yield variability in the
248 grid-based simulations compared to the point-based simulations (Fig S7). Solar radiation
249 inputs were 5% to 7% lower in the grid-based than in the point-based simulations (Fig. S3),
250 which might have contributed slightly to the simulated yield difference²⁴. Water stress was
251 not considered in either study for the comparison of these 30 locations and any possible
252 differences in precipitation inputs had no impact on the simulated results (Table S3). No
253 nitrogen stress was assumed in the point-based simulations, but four of the seven crop
254 models in the grid-based simulations did consider country-level average N fertilizer
255 application which could explain why the grid-based model ensemble simulated generally

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

257 Another important factor possibly contributing to yield differences between the
258 grid-based and point-based simulation at the local scale were the models used in the studies.
259 There were 29 crop models and one statistical regression in the point-based simulation
260 ensemble, whereas there were seven crop models in the grid-based simulations. Three models
261 (CERES, EPIC, and LPJmL) were common to both studies. These three models tended to
262 simulate lower yields than the 30-model ensemble average from the point-based study for the
263 30 locations, e.g., about $0.9 \text{ t}\cdot\text{ha}^{-1}$ less in the baseline period (Fig. S4). This may have lowered
264 the average simulated yields in grid-based simulations. Differences in the calibration of the
265 crop models would also affect simulations²⁵. Some models in the grid-based simulations were
266 calibrated and some were not, and especially growing periods were not harmonized across
267 grid-based models⁹, while in point-based simulations all models were calibrated for anthesis
268 and maturity dates with local phenology information⁸. Hence, differences in models, solar
269 radiation and inputs like N fertilizer may explain some of the lower yields found in the
270 grid-based studies. Differences in cultivar calibration, particularly for phenology and growing
271 season, adds another source of differences between these two studies.

272 **More yield reduction at warmer regions**

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

278 grid-based and point-based simulations were highly correlated. With 1°C global temperature
279 increase, higher yield reductions were observed at locations with higher baseline temperatures
280 than locations with lower baseline temperatures in both point-based and grid-based
281 simulations (Fig. 4c). For example, at Aswan in Egypt, point-based and grid-based
282 simulations showed about 11% and 20% decline in yield with 1°C temperature increase, while
283 for Krasnodar in Russia, point-based and grid-based simulations estimated about 4% and 7%
284 yield decline with 1°C global increase. The spatial pattern of temperature impacts at the
285 location scale was also consistent with that at the country scale (Fig. 2a, Fig. 2b, and Fig.S11),
286 which indicated that warmer regions (e.g. India) are likely to suffer more wheat yield
287 reductions than cooler regions (e.g. China). The exception is for statistical regression
288 estimates for Russia, a generally cooler region (Fig. 2b). The effects of temperature on wheat
289 yields are consistent with reports of impacts on other crops, such as maize, soybean, and
290 cotton^{26, 27, 28}. An increase in extreme temperature events with increasing mean temperatures²⁹
291 are likely to further contribute to yield decline in wheat^{30, 31}. Several crop models used in
292 point-based simulations (tested against warming experiments) and Regression_A (using a
293 nonlinear regression method), also considered the impacts of extreme temperature^{8, 10}.

294 **Effects of up-scaling methods**

295 To assess climate impacts on global or country-level crop production, both process-based
296 crop modeling approaches and statistical regressions need to be upscaled from locations to
297 regions and then to the entire globe³². In the point-based simulations, a range of local
298 information (e.g. local sowing dates, cultivar, anthesis and maturity date) was used for the 30
299 locations selected to represent about 70% of current global wheat production, which was then

300 upscaled via FAO statistics ⁸. Much less local information was available for each of the 0.5° ×
301 0.5° grid cells which were aggregated to country and global scales in the grid-based
302 simulations ⁹. However, very similar estimated temperature impacts on relative global yield
303 changes were simulated with both approaches. This was surprising as Ewert, van Bussel ¹⁴
304 showed that scaling methods can add significant uncertainties to simulated outcomes.
305 Although uncertainties are known to be reduced with multi-model ensembles, these results
306 might also indicate that the selected 30 locations in the point-based study ⁸ were indeed
307 representative of agro-climatic variability of wheat growing conditions throughout the world.
308 The results also suggest that global grid-based models, despite having limited local
309 information, are on a par with point-based approaches, while providing greater coverage of
310 regional heterogeneity.

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

317 **Advantage of different assessment methods**

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

322 regressions. Some of these factors might also be confounded in a statistical regression
323 analysis. While there have been attempts to include more factors in statistical impact methods
324 ³³, detailed process-based, dynamic crop simulation models may be more suitable to simulate
325 the more complex climate change scenarios, beyond the single impact of temperature change.
326 However, process-based models, like statistical methods, often do not account for many other
327 important factors required for holistic climate change impact assessment. Such factors include
328 impacts from frost, pests, weeds, diseases, and floods, and also dissimilar impacts between
329 day and night temperatures ³⁴, or extreme temperature events at different growth stages, which
330 are all likely to change with future climates. However, process-based models are capable of
331 accounting for the effects of elevated CO₂ ³⁵, even though this effect is not considered here,
332 but large uncertainties exist not only with respect to the general effects on crop yields ^{36, 37} but
333 also with respect to model implementation ^{9, 38}.

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

344 **Applying multi-method ensembles**

345 Understanding and quantifying uncertainty of impact assessments has been a key aspect
346 in assessing climate impacts on crop production in recent studies^{25, 42, 43}. Most previous studies
347 have focused on uncertainties arising from crop models or climate models²⁵. Here the
348 uncertainties in both point-based and grid-based simulations were quantified by multi-model
349 ensembles. Uncertainties due to crop models, expressed as error bars in the grid-based
350 simulations, were relatively large at both global and country scales (Fig. 1 & Fig. 3), which
351 was due to the limited number of models and relatively wide spread of model results in this
352 study. The differences in model inputs (e.g. nitrogen application, sowing dates, cultivars),
353 calibration methods and model⁹ explain some of the variability between the point and
354 grid-based simulations. Many crop models do not simulate temperature interactions with
355 canopy temperature variation under different soil water conditions, which could result in
356 simulated differences of temperature impacts⁸. However, multi-model ensemble medians
357 have been shown to be more consistently accurate than individual models when comparing
358 measurements across locations and growing environments, adding confidence to the estimates
359 here⁴⁴. Bootstrap resampling methods were employed to estimate the uncertainty of
360 temperature impacts calculated in the two global scale statistical regressions. Thus different
361 assessment approaches have independent methods of quantifying uncertainty. Multi-method
362 ensembles can enable the quantification of method uncertainty, similar to how multi-model
363 ensembles enable estimation of model uncertainty. The uncertainty range of wheat yield
364 reduction with 1°C global temperature increase from the multi-method ensemble calculated
365 from the median of the four methods analyzed here was between 4.0% and 6.9% at the global

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

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

376 Adaptation to global warming, e.g. farmer's autonomous adaptation through changing
377 sowing dates or cultivars, has been suggested in several studies to compensate negative
378 impacts of increasing temperature⁴⁶. At global scale, point-based simulations did not consider
379 adaptation. Also a panel regression approach attempted to exclude adaptations¹⁰. In the
380 grid-based simulations, four of the seven models did allow cultivar and sowing date
381 adaptation with a changing climate (Table S3), and the simulated impacts tended to be lower
382 with simulated adaptation (Fig.S10). However, temperature impacts from models with
383 adaptation varied largely. Temperature impacts with and without adaptation were estimated
384 from different models in grid-based simulations, which added considerable uncertainty in the
385 results. The adaptation effects on temperature impacts should be further studied with more
386 consistent protocols for multi-model assessments. Other future adaptation, e.g. wheat
387 cultivation shifting to marginal regions in higher latitudes, could offset some of the negative

388 impacts.

389 Assessing climate change impacts on crop production is a key aspect in determining
390 appropriate global food security strategies⁴². Reliable estimates of climate change impacts on
391 food security require an integrated use of climate, crop, and economic models¹⁵. Applying
392 multi-method ensembles further improves the estimated impact precision and confidence in
393 assessments of climate impacts on global food security. The consistent negative impact from
394 increasing temperatures confirmed by three independent methods warrants critical needed
395 investment in climate change adaptation strategies to counteract the adverse effects of rising
396 temperatures on global wheat production, including genetic improvement and management
397 adjustments^{47,48}. However, some or all of the negative global warming impacts on wheat
398 yield might be compensated by increasing atmospheric CO₂ concentrations under full
399 irrigation and fertilization²⁵.

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408

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419

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431

432 **Competing financial interests**

433 The authors declare no competing financial interests.

434

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- 614
- 615

616 **Figure legends**

617 **Figure 1 | Impacts of 1°C global temperature increase on global wheat yield**

618 **estimated by different assessment methods.** The grid-based ($0.5^\circ \times 0.5^\circ$ grid cells)

619 method is an ensemble median from seven global gridded crop models, averaged over

620 30 years and aggregated over all simulated grid cells (after Ref. 9). The point-based

621 method is an ensemble median from 30 models, averaged over 30 years and

622 aggregated over 30 global locations (after Ref. 8). Regression_A is based on a

623 country-level statistical regression from Ref. 10. Regression_B is based on a global

624 level statistical regression from Ref.11. The error bars for four different methods

625 indicate the 95% confidence intervals based on multi-model ensembles in the

626 simulations and bootstrap resampling in the statistical regressions. The mean of the

627 method_ensemble is shown with error bar indicating the 95% confidence intervals

628 based on medians of individual methods.

629

630 **Figure 2 | Comparison of wheat yield changes with 1°C global temperature**

631 **increase for 97 wheat producing countries estimated using three different**

632 **methods.** (a) Median simulations of a grid-based ($0.5^\circ \times 0.5^\circ$) ensemble of seven

633 models (after Ref. 9) versus a point-based (30 locations over 30 years) ensemble of 30

634 models (after Ref. 8). (b) Country level statistical regression for China, India, USA,

635 France and Russia, the top five wheat producing countries, from Ref. 10 versus

636 point-based simulations for these countries (after Ref. 8). Note, only data on these five

637 countries were supplied in Ref. 10. Circle color indicates the wheat growing season

638 temperature (from Ref. 10). Circle size indicates the amount of wheat production for
639 each country according to FAO statistics²³. The solid line is the 1:1 line and dashed
640 lines represent 0% yield change.

641

642 **Figure 3 | Estimated impacts of 1°C global temperature increase on wheat yield**

643 (a) China, (b) India, (c) Russia, (d) USA, and (e) France using different assessment
644 methods. The grid-based ($0.5^\circ \times 0.5^\circ$) method produced an ensemble median from
645 seven global gridded crop models (after Ref. 9). The point-based method produced an
646 ensemble median from 30 models from 1 to 3 country locations (after Ref. 8).

647 Regression_A is a statistical regression based on country statistics after Ref. 10.

648 Regression_C is a statistical regression based on $0.5^\circ \times 0.5^\circ$ grid statistics after Ref.

649 45. Regression_D is county level statistical regressions produced by two different

650 regression methods from Ref. 50. Regression_E is a county level regression produced

651 for this study. The error bars indicate the 95% confidence interval based on

652 multi-models for the simulations and bootstrap resampling (Regression_A,

653 Regression_B, and Regression_D) or t-tests (Regression_E) for the statistical

654 regressions. No error bar was provided for Regression_C in Ref. 45.

655

656 **Figure 4 | Comparison of simulated multi-model median wheat yield and yield**

657 **changes.** Absolute wheat yields for (a) baseline and (b) baseline + 1°C periods, and (c)

658 relative yield change with 1°C global temperature increase from grid-based

659 simulations ($0.5^\circ \times 0.5^\circ$) (from Ref. 9) of cells centered around the 30 locations from

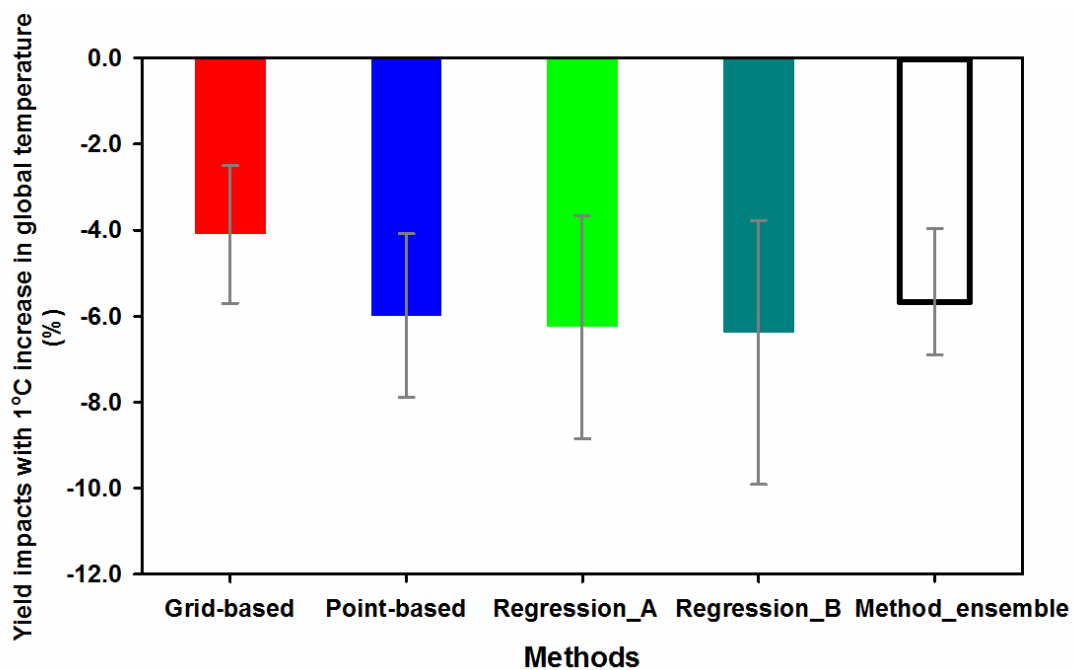
660 the point-based study versus that from the point-based simulations (from Ref. 8). Note

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

662

663

664 **Figure 1.**

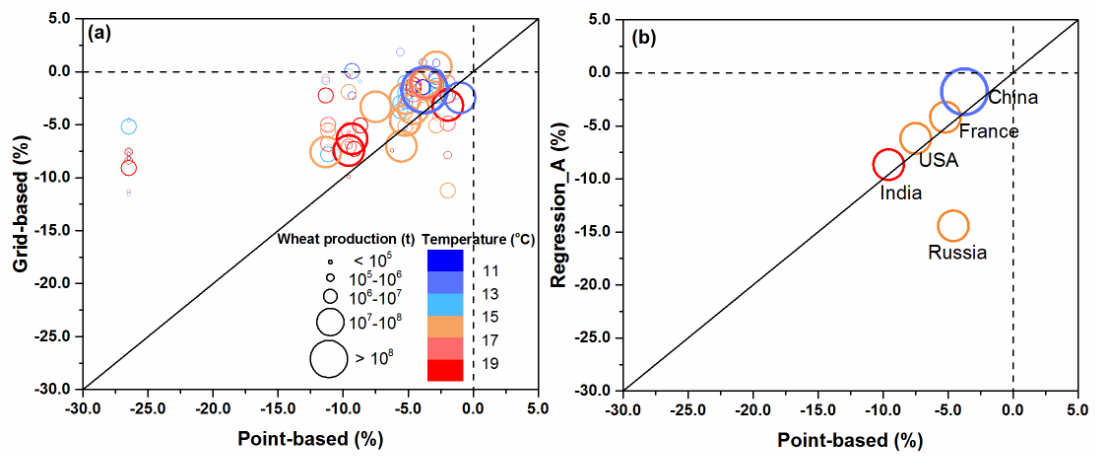


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668 **Figure 2.**

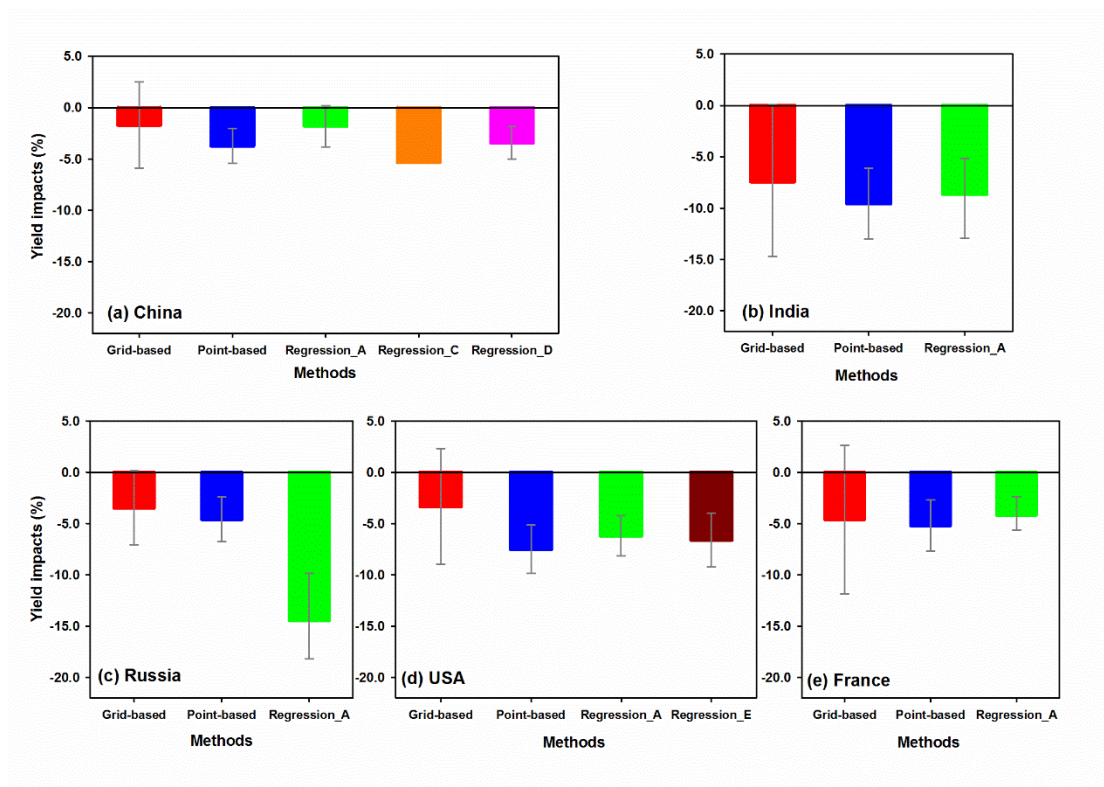


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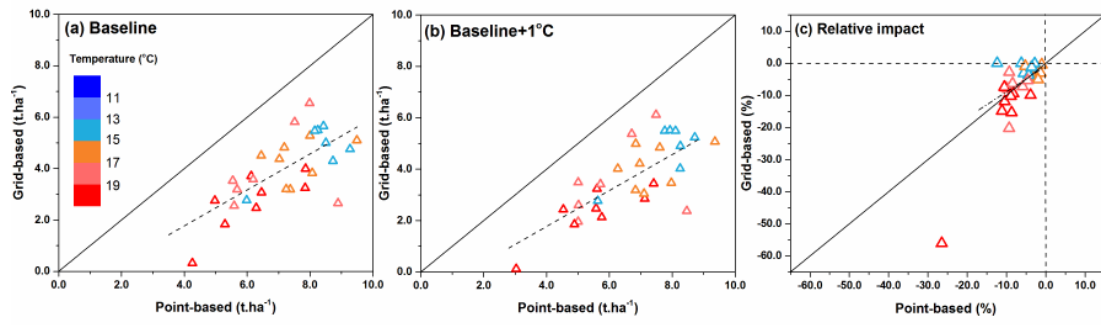
672 **Figure 3.**



673

674

675 **Figure 4.**



676

677

678 **Methods**

679 *Grid-based simulations.* Seven global gridded models simulated $0.5^\circ \times 0.5^\circ$ grid cells across
680 all wheat growing regions of the world from 1980 to 2099 under a RCP8.5 scenario with a
681 statistically-downscaled version of HadGEM2-ES⁴⁹, with only a small trend in solar radiation
682 at some locations (Fig. S6). Here, a set of simulation experiments without effects of elevated
683 CO₂ and under full irrigation treatments were used. Among the seven global gridded models,
684 adaptation through cultivars, sowing dates or growing season had been employed in four of
685 the models (Table S3). The global yield impacts from models with and without adaptation are
686 compared in Fig. S10. Only one climate model and RCP were used as there was limited data
687 available for grid-based simulations. The period 2029-2058 was selected as being on average
688 2°C warmer globally than the baseline period of 1981-2010 and the impact was halved to
689 adjust the temperature change to +1°C for the analysis here. The temperature change
690 considered here is 1°C warming of the global mean temperature, including land and ocean
691 surface. The change in simulated grain yields between these two temperature periods was
692 used to estimate temperature impacts on wheat at global and national scales. Grid-based
693 simulations for the direct comparison to point-based simulations were extracted from
694 simulations assuming full irrigation. For national and global scale results, grid-based
695 simulations were aggregated by area-weighted means, using rain-fed and irrigated wheat
696 areas per pixel of MIRCA2000⁵⁰ combining simulations under irrigated and rain-fed
697 conditions. To make projections between the different grid-based models comparable, yield
698 simulations were bias-corrected to national FAO levels by using FAO mean yields and
699 superimposing projected relative changes. More details about the grid-based simulations can

700 be found in Ref. 9.

701 *Point-based simulations.* Thirty models, 29 crop simulation models and one statistical
702 regression model, were used to simulate wheat grain yields for 30 representative locations in
703 high rainfall and irrigated wheat growing regions around the world (together representing
704 about 70% of global wheat production) with the estimated baseline period of 1981-2010 and
705 baseline + 2°C. Three models (CERES, EPIC, and LPJmL) in point-based simulations were
706 used in grid-based simulations. No CO₂ fertilization effects or any adaptation was considered
707 in the point-based simulations. The impact was halved to adjust the temperature change to
708 +1°C for the analysis here. Local temperature impacts on yields were adjusted to global
709 temperature change and upscaled via FAO statistics. Temperature impacts on national scales
710 were assessed for 125 countries. Each country was assigned as being similar to one or more
711 representative locations, so the temperature impacts of each country were the average impacts
712 of the corresponding representative locations. More details can be found in Ref. 8.

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

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

722 temperature used for the statistical regressions was also used here. The temperature factors are
723 listed in Table S1.

724 *Comparison at a national scale.* Temperature impacts for 97 countries from both grid-based
725 and point-based simulations were compared. Due to the limited number of country-scale
726 estimates of temperature impacts on wheat yields with statistical regression analysis, we
727 compared the regression results with the two simulation approaches for the top five wheat
728 producing countries (Table S1).

729 *Comparison at local scales.* Yield simulations from 30 single grid cells from the grid-based
730 method were chosen that were centered around the 30 global representative locations from the
731 point-based method. Full irrigation treatments were applied in point-based and grid-based
732 simulations. The baseline and increased temperature periods for the 30 grid cells were
733 determined individually by matching the 30-year average annual temperature of each grid to
734 the 30-year average annual temperature of the corresponding location from point-based
735 simulations. The baseline and increased temperature periods for each of the 30 grid cells and
736 temperature differences between the two methods are shown in Table S4. Most locations had
737 very similar temperature input data in the two comparison periods for grid-based and
738 point-based simulations. Outliers (Table S4) were found where the input data differed
739 substantially but these did not cause outliers in yield impacts. The yield impact outlier at the
740 Sudan location was caused by very low simulated yields (Fig. 4). The simulated yields for
741 baseline and increased temperature periods were used to calculate temperature impacts at the
742 local scale. These were also adjusted to global temperature change with the same method at
743 global and national scales. The temperature and radiation data from the critical growing

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

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

746

747