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

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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.

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

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

In further contrast, statistical regressions based on global and country level data have been used to quantify the impact of increasing temperatures on yields of wheat, maize, barley, soybean, sorghum and rice [10, 11]. An important difference from the simulation models is that statistical models do not directly consider processes inherent to crop growth. However, statistical models may include indirect effects of climatic variability, such as those related to pests and diseases, which are not well captured by simulation models [12]. When assessing climate effects on crop yields, crop models can take into account autonomous adaptation and an increase in atmospheric CO_2 concentration. Also some statistical regressions include the yield effects associated with autonomous adaptation [10]. For the effects of gradual increase in CO_2 concentration in the past, statistical models may inherently include these within yield effects [13], but for some regression models with a linear time term, effects of steady increase in CO_2 can be removed from yield impacts, just as the effects of technology improvement. In addition, upscaling methods influence the outcomes from regional assessments [14]. The statistical approach obtained global or regional impacts by aggregating county districts or countries [10, 11]. The grid-based system obtained global or regional impacts by aggregating $0.5^{o} \times 0.5^{o}$ grid cells [9], while the point-based approach employed 30 sites to represent global wheat regions [8]. Therefore, differences in upscaling could add uncertainties in the impact estimated in these studies.

In this letter, we compared three largely independent assessment methods used to estimate temperature impacts on wheat yields: grid-based simulations, point-based simulations, and statistical regressions. The details of each method are shown in Table S1. The methods used independent different dynamic, statistical, up-scaling and source data approaches. The grid-based simulations used here were from the Agricultural Model Intercomparison and Improvement Project (AgMIP) [15] as part of the Inter-Sectoral Impact 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^{o}C 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^{o}C 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^{o}C 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 estimated impacts do not increase linearly with increasing temperature and the disagreement among method estimates become larger with more temperature change (Fig. S9).

Impacts for major wheat-producing countries

To understand how the different methods project such similar temperature impacts on global wheat yields, we disaggregated the temperature impacts to the national scale. Point-based and grid-based simulations were compared for 97 countries (Fig. 2a). Generally, projected temperature impacts on wheat yields for most of the large wheat producers were similar between the two simulation methods (with a R^2 of 0.64 for the top 20 producers, Fig.S12), while differences were larger for small wheat-producing countries. Some large differences occurred between point-based and grid-based simulation in irrigated semiarid regions of Africa, which are mostly small wheat producers. The larger differences observed for smaller producers have little weight in the global analysis. However, they are important for regional economies. Method results were compared in more detail for the top five wheat producing countries (Fig. 2b, Fig. 3). For China, India, USA, and France, the different assessment methods resulted in similar values for temperature impacts on country wheat yields. Additional country-level studies relying on other methods and data sources gave similar estimates. For example, for China point-based simulations, grid-based simulations, and two different regressions all concluded that yield reductions of about 3.0% are expected with 1°C warming (Fig.3a). For India, country-level statistical regressions, grid-based and point-based simulations all estimated about 8.0% yield declines per °C of global temperature increase (Fig.3b). For Russia, the two simulation methods agreed well, but yield reductions estimated from statistical regression were markedly higher (Fig. 3c). Another study using statistical regression methods also showed higher negative temperature impacts on wheat yield than the two modeling methods used here for Rostov, a main wheat producing region in Russia [19]. Since wheat producing regions in Russia can experience relatively low temperatures (below optimal growth temperature) during early growing stages, a temperature increase during this stage (tillering), may have a positive yield impact, while at a later stage (booting or grain filling) an increase in temperature often reduces wheat yields [19]. As an average temperature over a growing season is usually used in statistical regressions, such in-season variability in temperature impacts would remain undetected. A dynamic crop simulation model takes in-season variability and impacts into account. This may explain the estimated larger impacts in Regression_A in comparison to the simulation results. For USA, a recent study using data from wheat variety trials from 1985–2013 in Kansas, USA reported a 7.3% decrease (corrected for global temperature change) in wheat yield with 1^{o}C global temperature increase[20]. This result is similar to the other estimated temperature impacts on wheat yields for the USA (Fig. 3d). For France, yield reduction estimates from grid-based simulations, point-based simulations, and statistical regressions were 4.6%, 5.2%, and 4.2%, respectively (Fig. 3e). In an independent study, a 0.42t.ha^{-1} reduction in wheat yields, which is a reduction of about 5.5% after correction for global temperature change, was reported in Northern France from 1998-2008 that included the planting of reference varieties in field experiments [21]. This is also in line with simulated impact response surfaces from a 26-wheat-model-ensemble across a European transect[22].

With the different temperature impact methods used, despite some variation, there is a 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 $0.5^o \times 0.5^o$ 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.

Applying multi-method ensembles

Understanding and quantifying uncertainty of impact assessments has been a key aspect in assessing climate impacts on crop production in recent studies[25, 42, 43]. Most previous studies have focused on uncertainties arising from crop models or climate models[25]. Here the uncertainties in both point-based and grid-based simulations were quantified by multi-model ensembles. Uncertainties due to crop models, expressed as error bars in the grid-based simulations, were relatively large at both global and country scales (Fig. 1 & Fig. 3), which was due to the limited number of models and relatively wide spread of model results in this study. The differences in model inputs (e.g. nitrogen application, sowing dates, cultivars), calibration methods and model [9] explain some of the variability between the point and grid-based simulations. Many crop models do not simulate temperature interactions with canopy temperature variation under different soil water conditions, which could result in simulated differences of temperature impacts [8]. However, multi-model ensemble medians have been shown to be more consistently accurate than individual models when comparing measurements across locations and growing environments, adding confidence to the estimates here[44]. Bootstrap resampling methods were employed to estimate the uncertainty of temperature impacts calculated in the two global scale statistical regressions. Thus different assessment approaches have independent methods of quantifying uncertainty. Multi-method ensembles can enable the quantification of method uncertainty, similar to how multi-model ensembles enable estimation of model uncertainty. The uncertainty range of wheat yield reduction with 1°C global temperature increase from the multi-method ensemble calculated from the median of the four methods analyzed here was between 4.0% and 6.9% at the global scale (95% confidence interval). While this absolute difference is still substantial, this is narrower than the uncertainty due to the models in the multi-model ensembles from the simulations or the boot-strapping method in the statistical regressions. Therefore, applying multi-method ensembles can improve reliability of the assessment of climate impacts on global food security.

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

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

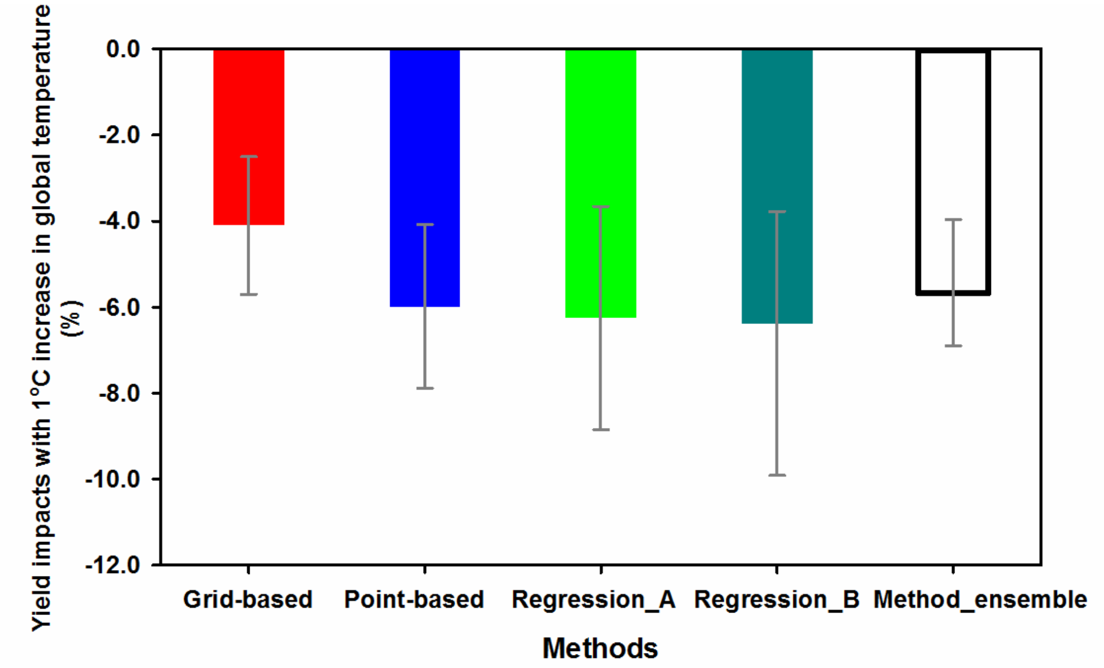
Figure 1 | Impacts of 1°C global temperature increase on global wheat yield estimated by different assessment methods. The grid-based (0.5° x 0.5° grid cells) method is an ensemble median from seven global gridded crop models, averaged over 30 years and aggregated over all simulated grid cells (after 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^{o}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} × 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} × 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.

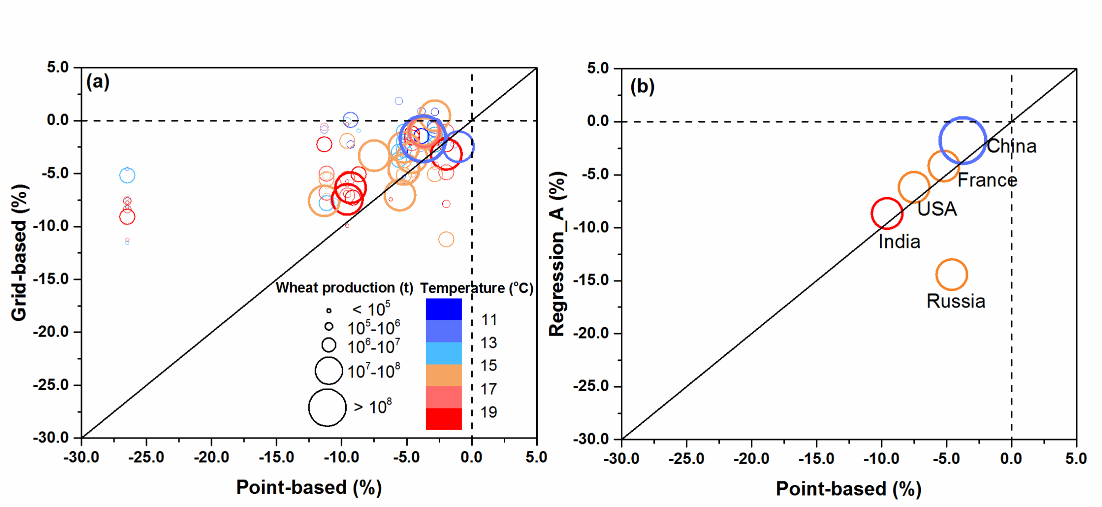
Figure 4 | Comparison of simulated multi-model median wheat yield and yield changes. Absolute wheat yields for (a) baseline and (b) baseline + 1^{o}C periods, and (c) relative yield change with 1^{o}C global temperature increase from grid-based simulations (0.5^{o} x 0.5^{o}) (from Ref. 9) of cells centered around the 30 locations from the point-based study versus that from the point-based simulations (from Ref. 8). Note in (c), regression line is drawn without outlier (location in Sudan).

Figure 1.



Yield impacts with 1°C increase in global temperature (%)
0.0
-2.0
-4.0
-6.0
-8.0
-10.0
-12.0
Grid-based
Point-based
Regression_A
Regression_B
Method_ensemble
Methods

Figure 2.



(a)
Grid-based (%)
Point-based (%)
Wheat production (t)
Temperature (°C)
< 10^5
10^5-10^6
10^6-10^7
10^7-10^8
> 10^8
11
13
15
17
19
(b)
Regression_A (%)
Point-based (%)
China
France
USA
India
Russia

Figure 3.

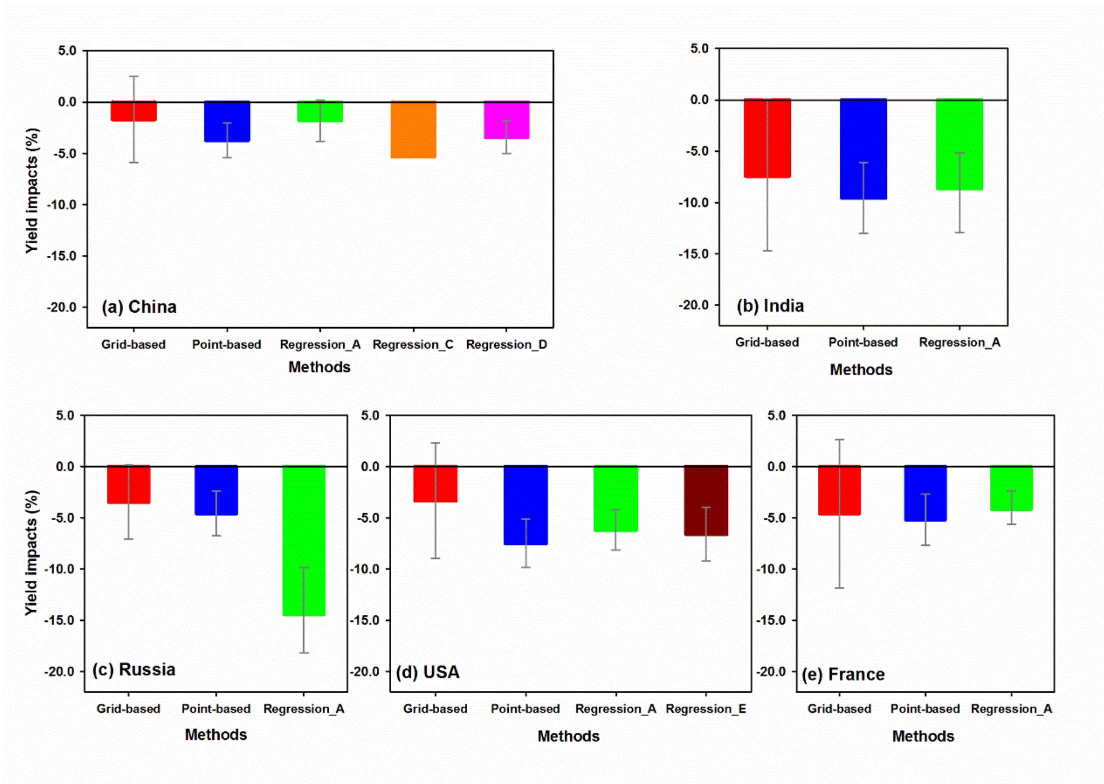
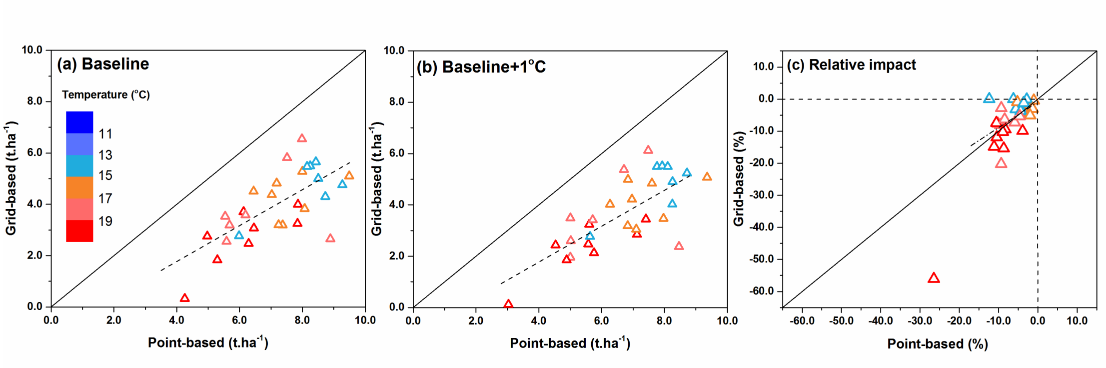

(a) China
(b) India
(c) Russia
(d) USA
(e) France
Yield impacts (%)
5.0
0.0
-5.0
-10.0
-15.0
-20.0
Grid-based
Point-based
Regression_A
Regression_C
Regression_D
Regression_E
Methods

Figure 4.


(a) Baseline
Temperature (°C)
11
13
15
17
19
Grid-based (t.ha^{-1})
Point-based (t.ha^{-1})
(b) Baseline+1°C
Grid-based (t.ha^{-1})
Point-based (t.ha^{-1})
(c) Relative impact
Grid-based (%)
Point-based (%)

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°C warmer globally than the baseline period of 1981-2010 and the impact was halved to adjust the temperature change to +1°C for the analysis here. The temperature change considered here is 1°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 be found in Ref. 9.

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

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

Meta-analysis and experimental data. Meta-analysis and experimental data from the literature are cited here for further comparison after adjusting them to global temperature change where possible. Meta-analysis and experimental data from the literature were cited here for further comparison after adjusting them to global temperature change. An adjustment factor to global temperature used for the statistical regressions was also used here. The temperature factors are listed in Table S1.

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

Comparison at local scales. Yield simulations from 30 single grid cells from the grid-based method were chosen that were centered around the 30 global representative locations from the point-based method. Full irrigation treatments were applied in point-based and grid-based simulations. The baseline and increased temperature periods for the 30 grid cells were determined individually by matching the 30-year average annual temperature of each grid to the 30-year average annual temperature of the corresponding location from point-based simulations. The baseline and increased temperature periods for each of the 30 grid cells and temperature differences between the two methods are shown in Table S4. Most locations had very similar temperature input data in the two comparison periods for grid-based and point-based simulations. Outliers (Table S4) were found where the input data differed substantially but these did not cause outliers in yield impacts. The yield impact outlier at the Sudan location was caused by very low simulated yields (Fig. 4). The simulated yields for baseline and increased temperature periods were used to calculate temperature impacts at the local scale. These were also adjusted to global temperature change with the same method at global and national scales. The temperature and radiation data from the critical growing period of wheat from 90 days before maturity to maturity were compared. Maturity dates were the dates supplied from observations for each location in the point-based method [8].