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**Title: Similar negative impacts of temperature on global wheat yield estimated by three independent methods**

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**Abstract**

The impact of global temperature change on global wheat production has recently been assessed with different methods, scaling and aggregation approaches. Here we show that grid-based simulations, point-based simulations, and statistical regressions produce similar estimates of temperature impact on wheat yields at global and national scales. With a 1°C global temperature increase, global wheat yield is projected to decline by between 4.1% and 6.0%, a relatively narrow range considering the different methods used. Projected temperature impacts from different methods were very similar for major wheat producing countries China, India, USA and France, but less so for Russia. At the location scale, the point-based method simulated higher responses to temperature than the grid-based method. Specifically, the point-based method tended to predict more yield loss with increasing temperature at cooler locations and less yield loss at warmer locations. However, both point- and grid-based simulations, and to some extent statistical regressions, were consistent in predicting that warmer regions are likely to suffer more yield reductions 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 when independent methods agree.

**Significance Statement**

Agricultural production is vulnerable to climate change and understanding climate change impacts is critical if policy makers, agriculturalists and breeders are to ensure global food security. This study compares climate impacts estimated by several different assessment methods. Our results show that independent methods produce very similar estimates of yield reductions with each degree of increase in global temperature, validating each impact method. Considering the different methods as a multi-method ensemble enhances the precision of the impact estimates by narrowing levels of uncertainty. As a result, confidence in the assessment of climate impacts on global food security is significantly improved.

Global demand for food is expected to increase 60% by the middle of the 21st century ([1](#_ENREF_1)). Climate change, and in particular rising temperatures, will impact food production ([2](#_ENREF_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](#_ENREF_3)). Some studies have shown regional impacts, e.g. for Europe ([4](#_ENREF_4)), China ([5](#_ENREF_5)), and Sub-Saharan Africa ([6](#_ENREF_6)). A few studies have considered impacts on the entire globe ([7-10](#_ENREF_7)). 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 ([7](#_ENREF_7), [8](#_ENREF_8)). While both studies used process-based crop simulation models, the scaling approach and input data were very different. The first study divided the globe into a geographical grid of cells defined by latitude and longitude and used climate and crop management data integrated over each grid as input for seven crop models ([7-10](#_ENREF_7)). 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 be representative of the various conditions found in wheat-producing areas worldwide ([7](#_ENREF_7)). In this point-based approach estimates from sentinel sites were scaled up and extrapolated to cover sites 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 ([9](#_ENREF_9), [10](#_ENREF_10)). An important difference from the simulation models is that statistical models do not directly consider processes inherent to crop growth. In addition, upscaling methods have shown to influence the outcomes form regional assessments ([11](#_ENREF_11)). The statistical approach obtained global or regional impacts by aggregating county districts or countries ([9](#_ENREF_9), [10](#_ENREF_10)). The grid-based system obtained global or regional impacts by aggregating 0.5° × 0.5° grid cells ([8](#_ENREF_8)), while the point-based approach employed 30 sites to represent global wheat regions ([7](#_ENREF_7)). Therefore, differences in upscaling could add uncertainties in the impacts assessments of these studies.

These three different impact methods are compared here at national and point scales to understand how methodological decisions could contribute to differences in estimated temperature impact on wheat crop yields at the global scale. Method results were then combined in a method ensemble to increase the precision and certainty of temperature impacts on global wheat production.

**Results and discussion**

We compared three largely independent assessment methods used to estimate temperature impacts on crop yields: grid-based simulations, point-based simulations, and statistical regression. 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 Intercomparison Project (AgMIP; 12) 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, over 0.5o × 0.5o grid cells ([8](#_ENREF_8)). The point-based simulations from the AgMIP-Wheat projects ([7](#_ENREF_7)) 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).

**Similar temperature impacts on global wheat yield are estimated by the three different methods.** The average reductions in global wheat production with 1°C global warming estimated from grid-based simulations, point-based simulations, statistical regression at country level, and statistical regression at global level were all between 4.1% and 6% (Fig. 1). The average estimated temperature impact from all three methods (and four studies) was a 5.1% reduction in global yield per degree of global temperature increase. The estimated temperature effects on global wheat production from the three different methods were similar (+/- ?).

Two meta-analyses of mostly process-based crop model simulations, reported a 4.9% decrease in global crop yields (combined wheat, rice, and maize) and a 3.3 ± 0.8% decrease in wheat yields with a 1°C increase in local temperature ([3](#_ENREF_3), [12](#_ENREF_12)). When adjusted to global temperature change. which is usually less than local wheat region temperature changes ([13](#_ENREF_13)), these impacts amount to 5.7% and 3.9% yield reduction per degree of global temperature increase, respectively. These values are very similar to the results obtained using the other three assessment methods reported herein.

**Different methods produce similar estimates of temperature impacts for major wheat producing countries.** To understand how these very different methods predict such similar temperature impacts on global wheat yields, we broke down 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 of most of the large wheat producers were similar with the two simulation methods, while differences were larger for small wheat-producing countries. The larger differences observed for smaller producers, nevertheless, have less weight in the global analysis. 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 very similar values for temperature impacts on country wheat yields. Additional country studies relying on other methods and data sources gave similar estimates. For example, 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 0.42 Mt.ha-1 reduction in wheat yields, which is a reduction of about 5.5% after correction for global temperature change, was reported from the GEVES-NT dataset in Northern France from 1998-2008 that included the planting of check varieties in field experiments ([14](#_ENREF_14)). Another 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°C global temperature increase ([15](#_ENREF_15)). This result is very similar to the other estimated temperature impacts on wheat yields for the USA (Fig. 3d). 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, although projections from district-level statistical regressions suggested a 15% yield reduction. A previous study estimated a similar range of yield reductions from 0.06 to 0.43 Mt ha-1 (about 2.6 to 17.4%) in four northwestern states of India ([16](#_ENREF_16)). These results may indicate a large spatial variability in temperature impacts across India. For Russia, the two simulation methods agreed well, but yield reductions estimated from statistical regression were markedly higher. A recent study using statistical methods also showed higher temperature impacts on winter wheat yields for Rostov, a main wheat producing region in Russia ([17](#_ENREF_17)). It is perhaps relevant to note that statistical models take into account the effects of warming on water stress, whereas the point-based and grid-based simulations used in this study only dealt with irrigated or high rainfall conditions, which are less representative of conditions in Russia ([18](#_ENREF_18)).

With the three 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 ([19](#_ENREF_19)), the similarity in method estimates of temperature impacts for these countries explains the similar negative temperature impacts computed at the global scale.

**Differences in model structure, model calibration, nitrogen management and cultivar characteristics explain most of the differences in simulated local grain yields**. At the local scale, the simulated yields from same-temperature periods from point-based and grid-based simulations were highly correlated (*P* < 0.001, R2 > 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%) Mt.ha-1 higher than in the corresponding grid-based simulations under baseline and baseline + 1°C conditions, respectively. In both studies, mean temperatures were similar for the period from 90 days before wheat maturity to maturity, except for three locations (Fig. S2). Seasonal temperature variability differed slightly between methods and caused a larger seasonal yield variability in the grid-based compared to point-based simulations (Fig S7). Solar radiation inputs were 5 to 7% lower in the grid- than point-based simulations (Fig. S3), which might have contributed slightly to the simulated yield difference ([20](#_ENREF_20)). Water stress was not considered in either study at these 30 global locations and any possible differences in precipitation inputs had no obvious impact on the simulated results (Table S3). Nitrogen fertilizer impacts were not considered in the point-based simulations, but four of the seven crop models in the grid-based simulations did consider country average N fertilizer application, which could explain why the grid- compared with point-based model ensemble simulates generally lower yields (Table S3).

Another important factor possibly contributing to yield differences between the grid- 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 7 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-base study for the 30 locations, about 0.9 Mt∙ha-1 less in the baseline period (Fig. S4). This may have lowered the grid-based simulations proportionally. Differences in the calibration of crop models can be another source for output differences ([21](#_ENREF_21)). Some models in the grid-based simulations were calibrated and some were not ([8](#_ENREF_8)), while in point-based simulations all models were calibrated for anthesis and maturity dates with local phenology information ([7](#_ENREF_7)). Hence, differences in model structure, solar radiation and inputs like N fertilizer could explain some of the lower yields found in the grid-based studies. Differences in cultivar calibration, particularly for phenology, add another source of differences between these two studies.

**Warmer regions likely to suffer more yield reductions with increasing temperature than** **cooler locations.** Interestingly, when comparing the grid- and point-based simulations the simulated relative yield impacts were more similar than simulated absolute yields (Fig. 4c and Fig. S1c). This was still true when the outlier location in Fig. 4c was removed from calculations. Temperature impacts at the local scale in grid- 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- and grid-based simulations. The spatial pattern of temperature impacts at the location scale was consistent with that at the country scale (Fig. 2), which indicated that warmer regions are likely to suffer more wheat yield reductions than cooler ones. The exception is for statistical regression estimates for Russia, a generally cooler region. The nonlinear effects of temperature on wheat yields are consistent with reports of impacts on other crops, such as maize, soybean, and cotton ([22-24](#_ENREF_22)). An increase in extreme temperature events with increasing mean temperatures ([25](#_ENREF_25)) are likely to further contribute to yield decline in wheat ([26](#_ENREF_26), [27](#_ENREF_27)).

**Temperature sensitivity of point- and grid-based simulations varies with background temperature.** Point- , rather than grid-based, simulations tended to predict more relative yield loss due to increasing temperature at lower background temperature locations and less yield loss at warmer locations. For example, at Aswan in Egypt, point-based simulations showed about 11% decline in yield with 1°C global temperature increase, compared to a 20% decline estimated from grid-based simulations. In contrast, for Krasnodar in Russia, point-based simulations estimated about 3% greater yield decline with 1°C global temperature increase than grid-based simulations. None of the models in these studies considered possible changes in frost risk with changing temperatures.

**Different upscaling methods have little effect on regional and global temperature impact assessments.** To assess climate impacts on global or country crop production, both process- and statistical-based regressions crop modeling approaches need to be upscaled from locations to regions and then to the entire globe ([28](#_ENREF_28)). For deterministic crop models used in grid- and point-based simulations, recent studies have suggested that a higher spatial resolution of input data improves model outputs by better representing critical spatial variability of climate impacts ([29](#_ENREF_29)). However, some input information for regional or global simulations, such as cultivars and crop management, are often difficult to obtain ([30](#_ENREF_30)). Low resolution input data often equates to a lower quality output. In the point-based simulations, a range of local information (e.g. local sowing dates, cultivar, anthesis and maturity date information) was used for the 30 locations selected to represent about 70% of current global wheat production, which was then upscaled via FAO statistics ([7](#_ENREF_7)). 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 ([8](#_ENREF_8)). However, very similar estimated temperature impacts on relative yield changes were simulated with both approaches. This was an unexpected result, since [Ewert*, et al.* (11)](#_ENREF_11) 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 ([7](#_ENREF_7)) 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 equivalent with point-based approaches, while providing greater coverage of regional heterogeneity.

**Advantages of validated methods to estimate impacts of temperature increase on wheat production.** 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 ([10](#_ENREF_10)) and country level yield data ([9](#_ENREF_9)) 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. Compared with process-based crop models, statistical regression models are simpler and require less input information. However, other important growth factors that are altered with climate change, such as increases in atmospheric CO2 concentrations or the combined effects of heat, water and nutrient stresses, all varying over the course of a crop growing cycle, are often not directly considered in statistical regression models. 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 ([31](#_ENREF_31)), detailed process-based, deterministic 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, still 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, which are all likely to change under future climates.

Field or controlled-environment experiments are independent ways to estimate temperature impacts on wheat yields ([7](#_ENREF_7), [12](#_ENREF_12)). For example, 2% to 8% reductions in wheat yield for every 1°C increase of post-anthesis temperature above an optimum season-average temperature of 15°C (i.e., local temperature change) have been measured for a range of cultivars under controlled-environment ([32](#_ENREF_32)) and field experiments ([33](#_ENREF_33)). 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 as such are not representative of a larger region, which make it difficult to extrapolate such measurements to regional or global impacts.

**Applying multi-method ensembles can improve the assessment of climate impacts on global food security**. Understanding and quantifying uncertainty of impact assessments has been a key aspect in assessing climate impacts on crop production in recent studies ([21](#_ENREF_21), [34](#_ENREF_34), [35](#_ENREF_35)). Most previous studies have focused on uncertainties arising from crop models or climate models ([21](#_ENREF_21)). Here the uncertainties in both point- 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 structures ([8](#_ENREF_8)) explain some of the large variability between the point- and grid-based simulations. However, using multi-model ensembles in point- and grid-based simulations added considerable confidence to the estimates, because multi-model ensemble medians have been shown to be more consistently accurate than individual models when comparing measurements across locations and growing environments ([36](#_ENREF_36)).

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 3.8% and 6.4% at the global scale (95% confidence interval). 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.

Assessing climate change impacts on crop production is a key aspect in determining appropriate global food security strategies ([34](#_ENREF_34)). Reliable estimates of climate change impacts on food security require an integrated use of climate, crop, and economic models ([37](#_ENREF_37)). Applying multi-method ensembles does further improve the estimated impact precision and confidence in assessments of climate impacts on global food security. Regional and global economic models require projected climate change impacts on crop production as inputs, hence the accuracy of these estimates can have significant consequences on economic estimates of grain supply, trade, price fluctuations, malnutrition and hunger in the world ([38](#_ENREF_38)).

**Materials and Methods**

**Data sources**

*Grid-based simulations*. Seven global gridded models simulated 0.5° × 0.5° 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 ([39](#_ENREF_39)), but without an elevated atmospheric CO2 effect and no trend in solar radiation (Fig. S6). 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 change in simulated grain yields between these two temperature periods was used to estimate temperature impacts on wheat at global and national scales. Simulated grid cells, assuming full irrigation (the grid-based simulation did not distinguish between the true irrigated and rainfed areas), were aggregated to generate results at country and global levels. More details about the grid-based simulations can be found in [Rosenzweig*, et al.* (8)](#_ENREF_8).

*Point-based simulations*.Thirty models, 29 crop simulation models and 1 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 °C. The impact was halved to adjust the temperature change to +1°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 [Asseng*, et al.* (7)](#_ENREF_7).

*Statistical regressions*. All estimated temperature impacts from statistical regressions were from literature reports, except for one new statistical regression analysis for the USA that we present herein. All temperature impacts were adjusted to global temperature change following the approach by [Asseng*, et al.* (7)](#_ENREF_7). Details of these regression studies 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.

*Comparison at a national scale.* Temperature impacts for 97 countries from both grid-based and point-based simulations were compared. For the major wheat producers only the top five countries were studied due to the limited number of country-scale estimations from statistical regressions (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. 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. There are some outliers (Table S4) where the input data differed substantially, but 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 priot to and at maturity were compared. Maturity dates were the dates supplied from observations for each location in the point-based method ([7](#_ENREF_7)).

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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 7 global gridded crop models, averaged over 30 years and aggregated over all simulated grid cells (after [Rosenzweig*, et al.* (8)](#_ENREF_8)). The point-based method is an ensemble median from 30 models, averaged over 30 years and aggregated over 30 global locations ([Asseng*, et al.* (7)](#_ENREF_7)). Regression\_A is based on a country-level statistical regression from [Lobell*, et al.* (9)](#_ENREF_9). Regression\_B is based on a global level statistical regression from [Lobell and Field (10)](#_ENREF_10). The error bars indicate the 95% confidence intervals based on multi-model ensembles in the simulations and bootstrap resampling in the statistical regressions.

**Figure 2.** Comparison of yield changes with 1°C global temperature increase for 97 wheat producing countries estimated using 3 different methods. (a) Median simulations of grid-based (0.5° × 0.5°) ensemble of 7 models (after [Rosenzweig*, et al.* (8)](#_ENREF_8)) versus point-based (30 locations over 30 years) ensemble of 30 models (after [Asseng*, et al.* (7)](#_ENREF_7)). (b) Country level statistical regression for China, India, USA, France and Russia, the top five wheat producing countries, from [Lobell*, et al.* (9)](#_ENREF_9) versus point-based simulations for these countries (after [Asseng*, et al.* (7)](#_ENREF_7)). Note, only data on these five countries were supplied in [Lobell*, et al.* (9)](#_ENREF_9). Circle color indicates the average annual temperature during the baseline period (1981-2010). Circle size indicates the amount of wheat production for each country according to FAO statistics ([19](#_ENREF_19)). 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 for (a) China, (b) India, (c) Russia, (d) USA and (e) France using different assessment methods. The grid-based (0.5° × 0.5°) method produced an ensemble median from 7 global gridded crop models (after [Rosenzweig*, et al.* (8)](#_ENREF_8)). The point-based method produced an ensemble median from 30 models from 1 to 3 country locations (after [Asseng*, et al.* (7)](#_ENREF_7)). Regression\_A is a statistical regression based on country statistics after [Lobell*, et al.* (9)](#_ENREF_9). Regression\_C is a statistical regression based on 0.5° × 0.5° grid statistics after [Xiong*, et al.* (40)](#_ENREF_40). Regression\_D and Regression\_E are both county level statistical regressions produced by different regression methods from [Zhang*, et al.* (41)](#_ENREF_41). Regression\_F is a county (district) level statistical regression after [Rao*, et al.* (42)](#_ENREF_42). Regression\_G 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, Regression\_D, and Regression\_E) or t-tests (Regression\_F and Regression\_G) for the statistical regressions. No error bar was provided for Regression\_C in [Xiong*, et al.* (40)](#_ENREF_40).

**Figure 4.** Comparison of simulated multi-model median wheat 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° x 0.5°) (from [Rosenzweig*, et al.* (8)](#_ENREF_8)) of cells centered around the 30 locations from the point-based study versus that from the point-based simulations (from [Asseng*, et al.* (7)](#_ENREF_7)). Note in (c), regression line is drawn without outlier (location in Sudan).

**Figure 1.**



**Figure 2.**

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**Figure 3.**



**Figure 4.**

