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Title:

Temperature increase reduces global yields of major crops in four independent estimates

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Abstract:

Wheat, rice, maize and soybean provide two-thirds of human caloric intake. Assessing the impact of global temperature increase on production of these crops is therefore critical to maintain global food supply, but different studies have yielded different results. Here we investigated the impacts of temperature on yields of the four crops by compiling extensive published results from four analytical methods: global grid-based and local point-based models, statistical regressions and field-warming experiments. Results from the different methods consistently show negative temperature impacts on crop yield at the global scale, generally underpinned by similar impacts at country and site scales. Without CO_2 fertilization, effective adaptation and genetic improvement, each degree Celsius increase in global mean temperature would on average reduce global yields of wheat by 6.0%, rice by 3.2%, maize by 7.4% and soybean by 3.1%. Results are highly heterogeneous across crops and geographical areas with some positive impact estimates. Multi-method analyses improved the confidence in assessments of future climate impacts on global major crops, and suggest crop- and region-specific adaptation strategies to ensure food security for an increasing world population.

Significance Statement

Agricultural production is vulnerable to climate change. Understanding climate change, especially the temperature impacts is critical if policy makers, agriculturalists and crop breeders are to ensure global food security. Our study, by compiling extensive published results from four analytical methods, show that independent methods consistently estimated negative temperature impacts on yields of four major crop at the global scale, generally underpinned by similar impacts at country and site scale. Multi-method analyses improved the confidence in assessments of future climate impacts on global major crops, with important implications for developing crop- and region-specific adaptation strategies to ensure future food supply of an increasing world population.

Crops are sensitive to climate change, including changes in temperature and precipitation, and to rising atmospheric CO_2 concentration, (1, 2). Among the changes, temperature increase has the most likely negative impact on crop yields (3, 4) and regional temperature changes can be projected from climate models with more certainty than precipitation. Meteorological records show that mean annual temperatures over areas where wheat, rice, maize and soybean are grown have increased by about 1 ^{o}C during the last century (Fig. 1A), and are expected to continue to increase over the next century (Fig. 1B), more so if greenhouse gas emissions continue to increase. It is thus necessary to quantify the impact of temperature increase on global crop yields, including any spatial variations, to first assess the risk to world food security, and then to develop targeted adaptive strategies to feed a burgeoning world population (5).

Several methods have been developed to assess the impact of temperature increase on crop yields (6). Process-based crop models characterize crop growth and development in daily time steps and can be used to simulate the temperature response of yield either in areas around the globe defined by grids or at selected field sites or points (3, 7). A third method, statistical modelling, uses observed regional yields and historical weather records to fit regression functions to predict crop responses (8, 9). A fourth method is to artificially warm crops under near-natural field conditions to directly measure the impact of increased temperatures (4). Here we combine these four methods, which use disparate data sources, time spans and up-scaling approaches (10), to assess the impact of increasing temperatures on yields of wheat, rice, maize and soybean. Grid-based and point-based simulations from recent international model intercomparison exercises (2, 7, 11, 12) and published results of 13 statistical regression studies and 54 field-warming experiments (Fig. S1) are synthesized (see Methods).

Results and discussion

Figure 2A illustrates the impact of temperature on yields of the four crops at the global scale. The loss in yield for each °C increase in global mean temperature is largest for maize (with multi-method average ±2 standard errors) of -7.4±4.5% per ^{o}C. All four methods predict a negative impact for maize, but with varying magnitudes. Mostly the different methods generated similar results at the country scale (Figs. 3C; S2-S3), but estimates varied between countries. The impact estimates are consistently negative for four major maize producers, together responsible for two-thirds of global maize production, namely the USA (-10.3±5.4% per ^{o}C), China (-8.0±6.1% per ^{o}C), Brazil (-5.5±4.5% per ^{o}C) and India (-5.2±4.5% per ^{o}C). The estimated impact on maize crops in France, however, is smaller (-2.6±6.9% per ^{o}C), including a small positive estimate (3.8±5.2% per ^{o}C) from statistical modelling (13).

For wheat, the average estimate from all four methods is a 6.0±2.9% loss in global yield with each ^{o}C increase in temperature (Fig. 2A). Results from the four methods agree more closely on the impact on wheat (-7.8 to -4.1% per °C) than on maize yields (Fig. 2A). The results from different methods are also generally consistent for the top five wheat-producing countries (Fig. 3A) that harvest over 50% of the world's wheat. Spatially, however, the impacts are highly heterogeneous. Estimated wheat yield losses for the USA (-5.5±4.4% per °C) and France (-6.0±4.2% per °C) are similar to the global average, while those for India (-9.1±5.4% per °C) and Russia (-7.8±6.3% per °C) are more vulnerable to temperature increase. The large yield reductions for Russia are mainly due to the contribution of a markedly higher negative result from the statistical method (-14.7±3.8% per °C; Fig. 3A), which did not account for in-season variations in temperature impact (10). By contrast, for China, the largest wheat producer in the world, the multi-method estimate indicates that only 2.6±3.1% of yield would be lost for each °C increase in global mean temperature.

Rice is a main source of calories in developing countries. The analysis from the multi-method ensemble indicates that a global increase in temperature of 1 °C will reduce global rice yield by an average of 3.2±3.7%, much less than for maize and wheat (Fig. 2A). Grid- and point-based simulations and field-warming experiments indicate a negative impact of temperature of about -6.0% per °C, but some statistical regressions suggest almost no impact. Similar disparities in estimates between the statistical regressions and the other methods are found for several major rice-producing countries (Fig. 3B), including China, which produces about 30% of the world's rice (14). Similar regression methods produce quite different estimates for Indonesia, Bangladesh and Vietnam, which when averaged across all methods lead to small estimated impacts on rice production for each country. For India, however, estimates from all methods predict large temperature impacts with a multi-method average of -6.6±3.8% per ^{o}C.

Soybean is the fourth most important commodity crop (14). Results of just three studies using only two methods are available for global-scale estimates of the impacts of temperature on soybean yield. The global average reduction in soybean yield is 3.1% per °C rise (Fig. 2A), but the estimates are not statistically significant due to large uncertainties in each method (the 95% CIs go through zero). Similar effects are estimated with both methods for the USA, Brazil, Argentina and Paraguay (Fig. 3D), which produce 84% of global soybean harvest (14). The largest expected reduction is -6.8±7.1% per °C for the USA, the largest soybean producer. The overall results for China, the fourth largest producer, however, do not indicate statistically significant effects of temperature on soybean yield.

We compared different methods for a total of ten sites and found that method estimates are similar for most site-crop combinations (Fig. 4). Estimates from grid- and point-based simulations are more similar to each other than to field-warming observations (Figs. 4 and S4). This is not unexpected as the two types of simulation have some methodological similarities, such as model structure, assumptions and parameters. The grid- and point-based models both tend to project greater yield loss with increasing temperature at warmer locations and less yield loss at cooler locations, a distinction not identified in the field experiments (Fig. S4).

Some of the impact differences between simulations and field experiments could be due to field experiments were only carried out over a few years and might not represent the entire variability of climate at this location while the simulations represent 30 years. Simulation parameters are also based on the properties of cultivars that differ from those grown in field experiments. For example, the field experiment in Wageningen (The Netherlands) indicated a large negative impact of temperature rise on wheat yield (-11.6% per °C) but used a spring wheat that is not representative of the region (15). Positive impacts (11.2±1.2% per °C) were observed in wheat warming experiments in

Nanjing, China, where rising temperatures reduce damage from frost and heat stress during the early and late experimental wheat growing seasons respectively (16), factors that are captured less well in crop models (17). For maize grown in Jinzhou (China), a field experiment and a regression analysis produced very large negative estimates of impact but were not accompanied by margins of error to aid interpretation.

We assumed the temperature response of impact on yield would be linear and multiplied projected temperature changes (Fig. 1B) with our multi-method impact estimates to give an average projected decrease in the global crop yields of 5.6% (95% CI, 0.1-14.4%) due to temperature change alone under the scenario of lowest emissions (RCP2.6) going up to 18.2% (95% CI, 0.7-38.6%) under the scenario of highest emissions (RCP8.5) (Fig. 2B). The estimated responses in yield are primarily from around +2 °C warming simulations, regressions and experiments (see Methods), so the estimates of impact for a global warming scenario near +4 °C (RCP8.5) are likely to be conservative due to the non-linear impact of rising temperatures in the real world (4, 18). A non-linear response to temperature has also been suggested in simulations (1, 7, 10).

To prepare for adaptation to climate change, it is necessary to isolate the effects of individual factor for possible impacts on yield, as changes in different factors usually require different adaptation strategies. While elevated atmospheric CO_2 concentration can stimulate growth when nutrients are not limited, it will also increase canopy temperature from more closed stomata (19). Also changes in precipitation can have an effect on crops, but projections on precipitation change are often uncertain. The focus of our study is on temperature change, one of the most direct negative impact from climate change on crops, and does not include other possible climate change effects from elevated atmospheric CO_2 concentration or changes in rainfall, and possible deliberate adaptation taken by farmers. Farmers have increased yields through adapting new technologies during the last half century, but yield has been also lost through increases in temperatures already (8). Yield increase has slowed down or even stagnated during last years in some parts of the world (20, 21) and further increases in temperature will result in further decreases in observed yields, in spite of farmers' adaptation efforts.

The direct negative temperature impact on yield could be additionally affected via indirect temperature impacts. For instance, increasing temperature will increase atmospheric water demand, which could lead to additional water stress from increased water pressure deficits, subsequently reducing soil moisture and decreasing yield (22, 23). However, an accelerated phenology from increased temperatures leads to a shorter growing period and less days of crop water use within a cropping season. Such indirect temperature effects are taken into account in each of the methods but are not explicitly quantified. Other indirect temperature impacts include more frequent heat waves and possible temperature impact on weeds, pests and diseases (18, 24-26). Increases in management intensity and yield potential could also unintentionally increase yield sensitivity to weather (27).

By combining four different methods, our comprehensive assessment of the impacts of increasing temperatures on major global crops shows substantial risks for agricultural production, already stagnating in some parts of the world (20, 21).

However, differences in temperature responses of crops around the world suggest some mitigation could be possible to substantially affect the magnitude (or even direction) of climate change impacts on agriculture. These impacts will also vary substantially for crops and regions, and may interact with changes in precipitation and CO_2, so a reinvigoration of national research and extension programs is urgently needed to offset future impacts of climate change, including temperature increase on agriculture using crop- and region-specific adaptation strategies.

Materials and Methods

Temperature data

Historical observed gridded monthly temperature data are from the Climate Research Unit (0.5° × 0.5° grid, CRU TS 3.23; https://crudata.uea.ac.uk/cru/data/temperature/). Future predicted temperature data are from the Coupled Model Intercomparison Project Phase 5 (CMIP5) Earth System Models (ESMs) outputs (1.0° × 1.0° grids; http://cmip-pcmdi.llnl.gov/cmip5) used in the IPCC AR5 (28). According to data availability, the outputs from 15, 20, 11 and 22 ESMs were included in this study for RCP2.6, RCP4.5, RCP6.0 and RCP8.5 scenarios, respectively. However, the calculated temperature changes are very similar to those calculated using all the ESMs (IPCC 5). The annual mean temperature over the global growing area of an individual crop was calculated by weighting each grid cell average (0.5° × 0.5° grids) according to the crop growing area within the grid cell (29).

Global gridded crop model simulations

The Agricultural Model Intercomparison and Improvement Project (AgMIP) (30) and Inter-Sectoral Impact Model Intercomparison Project 1 (ISI-MIP-1) (31) initiated a fast-track global climate impact assessment for the main global crops in 2012, including wheat, rice, maize and soybean. Seven global gridded crop models were used to simulate crop yield in $0.5^o \times 0.5^o$ grid cells over the globe, forced with climate reconstruction for 1980-2099 based on HadGEM2-ES (32) derived from CMIP5. The simulations were carried out under a scenario of constant CO_2 concentration (380 ppm in 2000) and full irrigation, to exclude the possibility of covariance with CO_2 and precipitation. More detailed information about the simulations can be found in (1, 33). Temperature impact values were calculated from yield changes between 2029-2058 (+2 ^oC of global mean temperature) and 1981-2010 (baseline) which were then halved to give +1 ^oC of global temperature impact. For global or country results, all the grids were averaged by weighting the corresponding growing area of each crop (29).

Point-based ensemble simulations

The Agricultural Model Intercomparison and Improvement Project (AgMIP) (30) also conducted crop yield simulations at 30, 4 and 4 representative sites around the world (Fig. S1) by using 30 wheat, 13 rice and 19 maize models, respectively. For wheat, a scenario of +2 ^oC was created by adjusting each day's temperature by +2 ^oC relative to the baseline (1981-2010), other factors being constant. For rice and maize, the +3 ^oC scenarios were used. Model details about simulations for each crop can be found in refs 7, 11 and 12. The temperature impact was calculated as the yield change during the warming period relative to the yield during the baseline period normalized to +1 ^oC impact, assuming impact showed a linear temperature response. To obtain values for impacts at the country scale, each country was deemed to be similar to one or more representative sites located in said (or nearby) country. As local temperature change can be different to the country mean, the local point-based estimates were scaled up by multiplying each country's temperature factor produced by HagGEM2-ES (28), as in ref. 7. The weighted average temperature impacts over all the countries were used to estimate the globe scale impact, weighted by country-level production (14). It should be noted that the results from only 4 sites were used to represent all the rice/maize-producing countries, which might not encompass all the uncertainties from diverse production systems and is also one limitation in our analysis. No point-based model-ensemble simulations for soybean were conducted in AgMIP.

Field-warming experiments

We started with all published peer-reviewed studies that applied artificial warming treatments on field crops. To avoid short-term noise, we only selected studies of crops that received all-day warming treatments for more than two months. Results from laboratory incubators or controlled environments with constant day-night temperature treatment (e.g., 37/29 ^{o}C vs. 29/21 ^{o}C) were excluded. The studies with temperature change (ΔT) unequal to +1 ^{o}C were adjusted to +1 ^{o}C impact by dividing the impact value by ΔT, which assumed a linear relationship between impacts and ΔT. The studies that produced temperature impacts of more than 50% per ^{o}C were deemed as outliers and excluded. A total of 46 published studies (available from the corresponding author on reasonable request) and 48 sites (Fig S1) were therefore included in the following analysis. Most of the sites (41 out of 48) had a warming magnitude of 1.5-3.0 ^{o}C, similar to the grid-based and point-based simulations. The upscaling methods from site to country to global scale are the same as for the point-based model simulations.

Statistical regressions

Statistical models used regression equations to link historical year-to-year variations in yield to variations in selected climate variables. Different detrending methods were applied in the model to remove the influence of adaptation measures, such as crop management. In the statistical regression studies used here, the global level results of regression A and B (Fig. 2A) used detrending methods with the inclusion of a quadratic time trend and first-differences, respectively, and resulted in more similar temperature impacts than grid- or point-based simulations. A similar result was found for the country-level regression A and C (the country level results in Fig. 3), which used detrending methods with inclusion of a quadratic time trend and first-differences method, respectively. The results from statistical models were from 13 published studies (available from the corresponding author on reasonable request). The interannual fluctuation in temperature over the globe is around 2 °C (8), similar to the warming magnitude used in other methods. To ensure comparability of results, reported values under local temperature changes were normalized to global surface temperature changes by multiplying the corresponding temperature factor produced by HagGEM2-ES (28).

Multi-method ensemble

The above four methods constituted the method ensemble that we used to estimate multi-method means and uncertainties. In this study, values from the method ensembles were synthesized at site, country and global scale. At the country scale, the temperature impacts from regression methods were only reported for the five countries producing each crop, thus the results mainly focus on the relevant top five countries. The uncertainty for the method ensemble was calculated by using a formula: var(Y) = var(E(Y|method)) + E(var(Y|method)), where the term (var(E(Y|method))) is a measure of the variability between methods, and E(var(Y|method)) is a measure of the average variability within methods, assuming that this is random sample of approaches from a population of approaches. Confidential intervals (CI) at 95% were calculated for the multi-method mean as: 95% CI = mean of methods $\pm 1.96\times\sqrt{\mathrm{var(Y)}}$.

Comparisons between methods

A recent study by Liu *et al.*, 2016 (10) compared the temperature impacts on wheat yield estimated by three different methods. We extended the analyses by including a large number of datasets from site-based observations (field-warming experiments) and comparing estimated impacts on yields of wheat, rice, maize and soybean, the four most important staple crops for humans. At the country scale, different methods were compared across countries. For the regression method, the results were only reported for the five major countries producing each crop and thus the comparisons only focused on the relevant five countries. At the site scale, grid-based simulations were compared with site-based simulations and field-warming experiments. Grids containing sites of point-based simulations or warming experiments were selected. The comparisons include absolute yield under different temperature scenarios and relative temperature impacts. The baseline and temperature period for each grid was determined when the rolling 30-year annual mean temperature was equal to the baseline and increased temperatures used for point-based simulations and experiments. The temperature impact was calculated as the yield changes relative to the baseline and then adjusted to a +1 ^{o}C global temperature impact.

Prediction of yield changes by the end of century

The yield change by the end of century was calculated as the products of the ensemble estimated yield response and projections of global temperature rise from CMIP5. As the yield response (Fig. 2A) and predicted temperature change (Fig. 1B) both have uncertainties, a bootstrap resampling approach was used to obtain the predicted yield change and its uncertainty. At each instance of bootstrap resampling, one pair of values for yield response and temperature change were sampled respectively from their original data to calculate the predicted yield change; this procedure assumes the chosen value is a random sample from a population of values. Repeating the above process 5000 times gave 5000 values of predicted yield change, which constitute a new distribution of the predicted yield change. The 2.5th to 97.5th percentile were deemed as the boundaries of uncertainty for the predicted yield change.

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Footnotes

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The authors declare no competing financial interests.

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Figure legends

Figure 1. Mean annual temperature changes over time. (**A**) Historically observed temperature anomalies relative to 1961-1990 for global growing areas of four individual crops. (**B**) Future projected temperature changes (2071–2100 in comparison to 1981–2010 baseline) of four crop-growing areas and the globe (land and sea surface) under four representative concentration pathway (RCP) scenarios of increasing greenhouse gas concentrations. Error bars represent standard deviations in the climate model results.

Figure 2. **Multi-method estimates of global crop yield changes in response to temperature increase.** (**A**) Impacts on crop yields of a 1 °C increase in global temperature in grid-based simulations (Grid-Sim), point-based simulations (Point-Sim), field-warming experiments (Point-Obs), and statistical regressions at the country level (Regres_A) (9) and the global level (Regres_B) (8). Circles, means of estimates from each method or medians for Grid-Sim and Point-Sim. Filled bars, means of the multi-method ensemble. Error bars show 95% CIs for individual methods (grey lines) and the ensemble of methods (black lines). (**B**) Projected changes in yield due to temperature changes by the end of the 21st century. CIs of 95% are given in square brackets.

Figure 3. **Multi-method estimates of grain yield changes with a 1 ºC increase in global temperature for the five major countries producing each crop.** (**A**) Wheat. (**B**) Rice. (**C**) Maize. (**D**) Soybean. Grid-Sim, Point-Sim Point-Obs and Regres_A are grid-based simulations, point-based simulations, field-warming experiments and statistical regressions at the country level (Regres_A) (9), respectively. Regres_C is another regression method used at the country scale (13). Regres_D-K represents

various country-level regression analyses used for specific crops or countries shown by individual labels D-K above the bars. Vertical axes show the temperature impact on crop yield in % per ^{o}C increase. Error bars are 95% CIs. Values for error margins are not available for point-based observations for maize in China.

Figure 4. **Site-based multi-method ensemble of crop yield changes with 1 ^{o}C of global temperature increase**. Site estimates from >3 methods are shown for (**A**) wheat, (**B**) rice and (**C**) maize or from 2 methods for (**D**) soybean. Grid-Sim, Point-Sim and Point-Obs are grid-based simulations, point-based simulations and field-warming experiments, respectively. Regres_L-N are site-, county- or city-scale regression analyses for specific crops shown by labels L-N next to the mean of the plotted dataset. Error bars are 95% CIs. Error bars for the Jinzhou (China) results for regression L and N were not available.

524 **Figure 1**

525

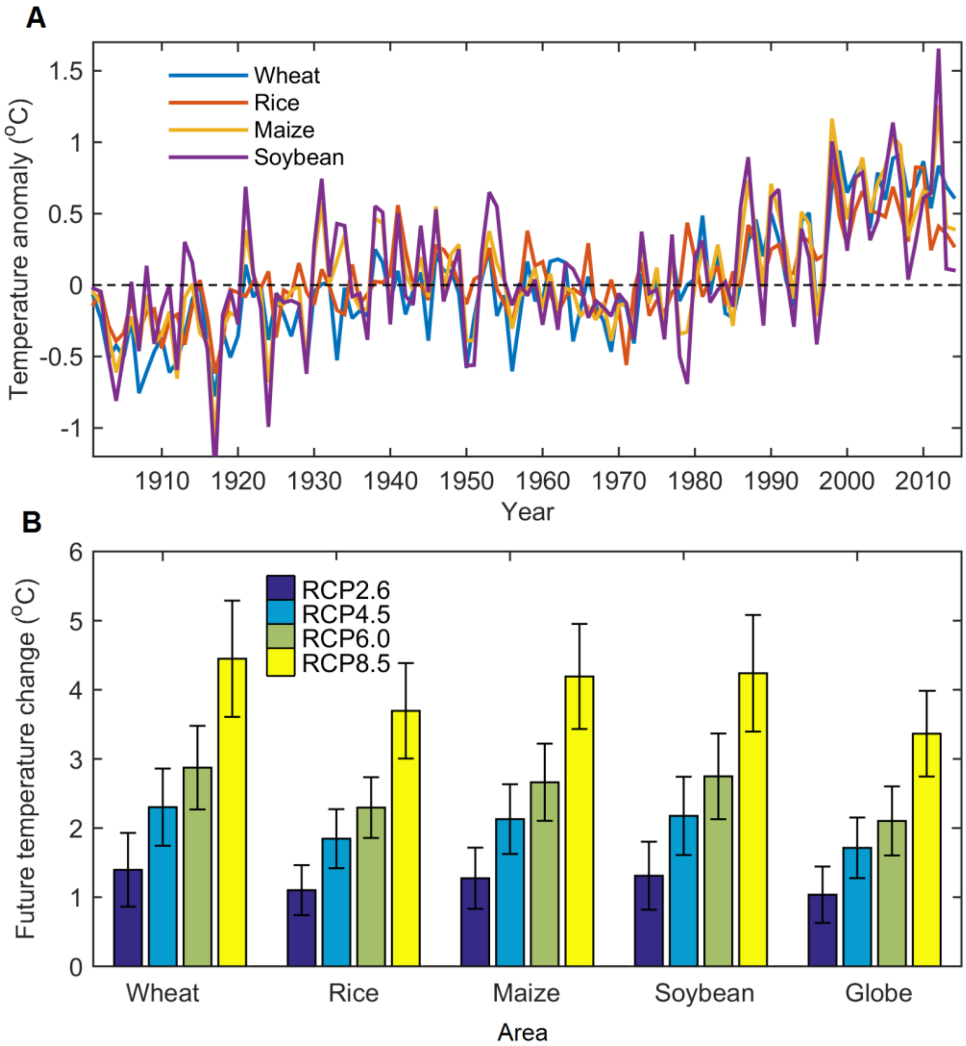
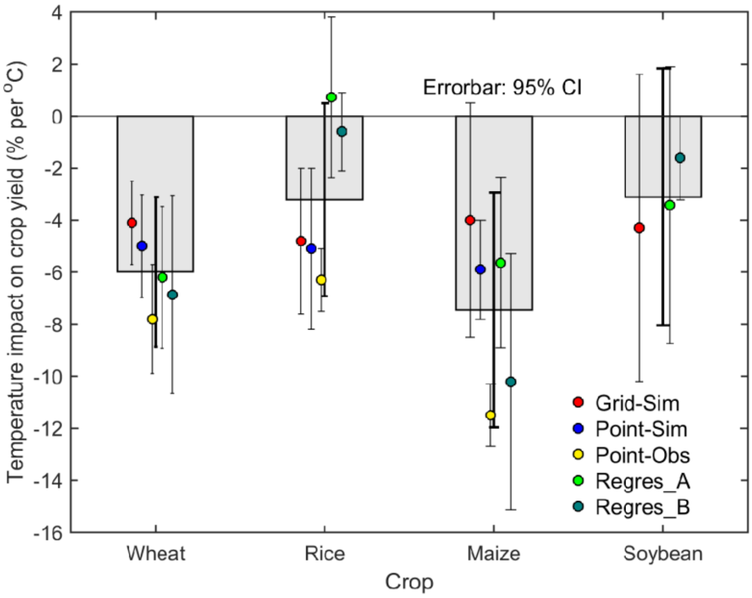


Figure 2

A



B

	Yield changes (%) due to temperature changes by the end of century				
Scenario	Wheat	Rice	Maize	Soybean	Mean
RCP2.6	-6.9 [-15.0, -1.4]	-3.3 [-9.2, 0.8]	-8.6 [-18.6, -1.8]	-3.6 [-11.2,1.7]	-5.6 [-14.4, -0.1]
RCP4.5	-11.4 [-21.7, -3.9]	-5.5 [-13.8, 1.0]	-14.2 [-27.9, -4.9]	-5.9 [-17.0, 3.1]	-9.2 [-21.2, -0.3]
RCP6.0	-14.0 [-25.7, -5.1]	-6.8 [-16.8, 1.3]	-17.4 [-33.1, -5.8]	-7.2 [-20.2, 3.6]	-11.3 [-25.6, 0.1]
RCP8.5	-22.4 [-40.2, -8.5]	-10.8 [-25.3, 2.4]	-27.8 [-50.4, -9.7]	-11.6 [-31.0, 6.0]	-18.2 [-38.6, -0.7]

Figure 3

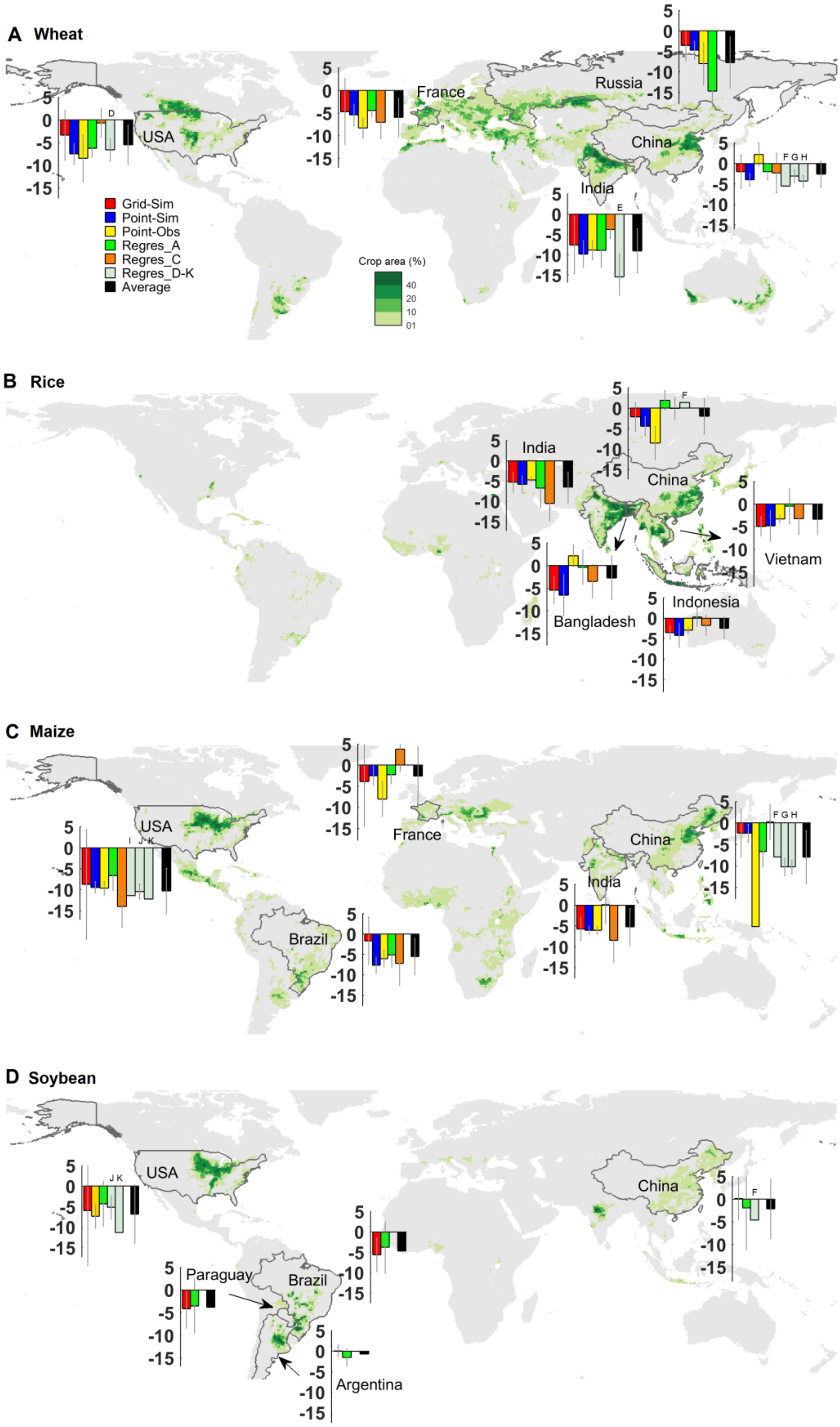
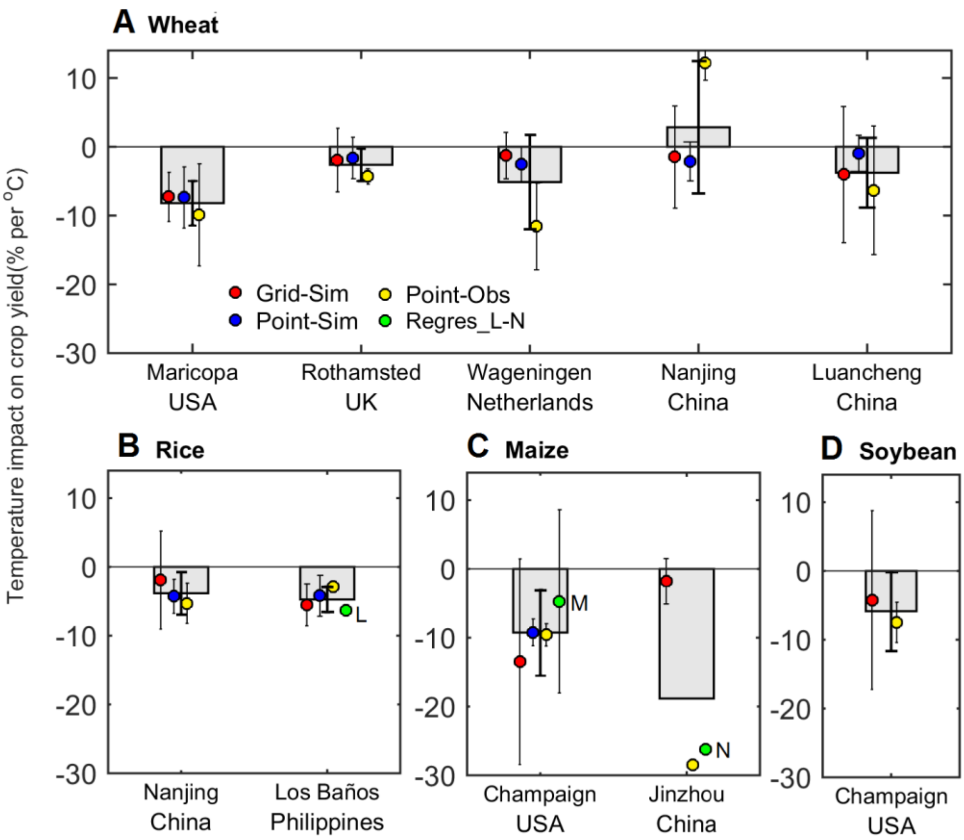

A Wheat
USA
France
Russia
China
India
Grid-Sim
Point-Sim
Point-Obs
Regres_A
Regres_C
Regres_D-K
Average
Crop area (%)
40
20
10
01
B Rice
India
China
Vietnam
Bangladesh
Indonesia
C Maize
USA
France
China
India
Brazil
D Soybean
USA
China
Paraguay
Brazil
Argentina

Figure 4



A Wheat
B Rice
C Maize
D Soybean
Temperature impact on crop yield(% per °C)
Grid-Sim
Point-Sim
Point-Obs
Regres_L-N
Maricopa
USA
Rothamsted
UK
Wageningen
Netherlands
Nanjing
China
Luancheng
China
Nanjing
China
Los Baños
Philippines
Champaign
USA
Jinzhou
China
Champaign
USA
L
M
N
10
0
-10
-20
-30