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2

3 **Title:**

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

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68

69 **Abstract:**

70 Wheat, rice, maize and soybean provide two-thirds of human caloric intake.
71 Assessing the impact of global temperature increase on production of these crops is
72 therefore critical to maintain global food supply, but different studies have yielded
73 different results. Here we investigated the impacts of temperature on yields of the four
74 crops by compiling extensive published results from four analytical methods: global
75 grid-based and local point-based models, statistical regressions and field-warming
76 experiments. Results from the different methods consistently show negative temperature
77 impacts on crop yield at the global scale, generally underpinned by similar impacts at
78 country and site scales. Without CO₂ fertilization, effective adaptation and genetic
79 improvement, each degree Celsius increase in global mean temperature would on
80 average reduce global yields of wheat by 6.0%, rice by 3.2%, maize by 7.4% and
81 soybean by 3.1%. Results are highly heterogeneous across crops and geographical areas
82 with some positive impact estimates. Multi-method analyses improved the confidence in
83 assessments of future climate impacts on global major crops, and suggest crop- and
84 region-specific adaptation strategies to ensure food security for an increasing world
85 population.

86

87

88 **Significance Statement**

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

99

100

101 Crops are sensitive to climate change, including changes in temperature and
102 precipitation, and to rising atmospheric CO₂ concentration, (1, 2). Among the changes,
103 temperature increase has the most likely negative impact on crop yields (3, 4) and
104 regional temperature changes can be projected from climate models with more certainty
105 than precipitation. Meteorological records show that mean annual temperatures over
106 areas where wheat, rice, maize and soybean are grown have increased by about 1 °C
107 during the last century (Fig. 1A), and are expected to continue to increase over the next
108 century (Fig. 1B), more so if greenhouse gas emissions continue to increase. It is thus
109 necessary to quantify the impact of temperature increase on global crop yields,
110 including any spatial variations, to first assess the risk to world food security, and then
111 to develop targeted adaptive strategies to feed a burgeoning world population (5).

112

113 Several methods have been developed to assess the impact of temperature increase
114 on crop yields (6). Process-based crop models characterize crop growth and
115 development in daily time steps and can be used to simulate the temperature response of
116 yield either in areas around the globe defined by grids or at selected field sites or points
117 (3, 7). A third method, statistical modelling, uses observed regional yields and historical
118 weather records to fit regression functions to predict crop responses (8, 9). A fourth
119 method is to artificially warm crops under near-natural field conditions to directly
120 measure the impact of increased temperatures (4). Here we combine these four methods,
121 which use disparate data sources, time spans and up-scaling approaches (10), to assess
122 the impact of increasing temperatures on yields of wheat, rice, maize and soybean. Grid-
123 based and point-based simulations from recent international model intercomparison

124 exercises (2, 7, 11, 12) and published results of 13 statistical regression studies and 54
125 field-warming experiments (Fig. S1) are synthesized (see Methods).

126

127 **Results and discussion**

128 Figure 2A illustrates the impact of temperature on yields of the four crops at the
129 global scale. The loss in yield for each °C increase in global mean temperature is largest
130 for maize (with multi-method average ± 2 standard errors) of $-7.4 \pm 4.5\%$ per °C. All four
131 methods predict a negative impact for maize, but with varying magnitudes. Mostly the
132 different methods generated similar results at the country scale (Figs. 3C; S2-S3), but
133 estimates varied between countries. The impact estimates are consistently negative for
134 four major maize producers, together responsible for two-thirds of global maize
135 production, namely the USA ($-10.3 \pm 5.4\%$ per °C), China ($-8.0 \pm 6.1\%$ per °C), Brazil ($-$
136 $5.5 \pm 4.5\%$ per °C) and India ($-5.2 \pm 4.5\%$ per °C). The estimated impact on maize crops in
137 France, however, is smaller ($-2.6 \pm 6.9\%$ per °C), including a small positive estimate
138 ($3.8 \pm 5.2\%$ per °C) from statistical modelling (13).

139

140 For wheat, the average estimate from all four methods is a $6.0 \pm 2.9\%$ loss in global
141 yield with each °C increase in temperature (Fig. 2A). Results from the four methods
142 agree more closely on the impact on wheat (-7.8 to -4.1% per °C) than on maize yields
143 (Fig. 2A). The results from different methods are also generally consistent for the top
144 five wheat-producing countries (Fig. 3A) that harvest over 50% of the world's wheat.
145 Spatially, however, the impacts are highly heterogeneous. Estimated wheat yield losses
146 for the USA ($-5.5 \pm 4.4\%$ per °C) and France ($-6.0 \pm 4.2\%$ per °C) are similar to the global
147 average, while those for India ($-9.1 \pm 5.4\%$ per °C) and Russia ($-7.8 \pm 6.3\%$ per °C) are

148 more vulnerable to temperature increase. The large yield reductions for Russia are
149 mainly due to the contribution of a markedly higher negative result from the statistical
150 method ($-14.7 \pm 3.8\%$ per $^{\circ}\text{C}$; Fig. 3A), which did not account for in-season variations in
151 temperature impact (10). By contrast, for China, the largest wheat producer in the world,
152 the multi-method estimate indicates that only $2.6 \pm 3.1\%$ of yield would be lost for
153 each $^{\circ}\text{C}$ increase in global mean temperature.

154

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

167

168 Soybean is the fourth most important commodity crop (14). Results of just three
169 studies using only two methods are available for global-scale estimates of the impacts of
170 temperature on soybean yield. The global average reduction in soybean yield is 3.1%
171 per $^{\circ}\text{C}$ rise (Fig. 2A), but the estimates are not statistically significant due to large

172 uncertainties in each method (the 95% CIs go through zero). Similar effects are
173 estimated with both methods for the USA, Brazil, Argentina and Paraguay (Fig. 3D),
174 which produce 84% of global soybean harvest (14). The largest expected reduction is -
175 $6.8 \pm 7.1\%$ per °C for the USA, the largest soybean producer. The overall results for
176 China, the fourth largest producer, however, do not indicate statistically significant
177 effects of temperature on soybean yield.

178

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

187

188 Some of the impact differences between simulations and field experiments could be
189 due to field experiments were only carried out over a few years and might not represent
190 the entire variability of climate at this location while the simulations represent 30 years.
191 Simulation parameters are also based on the properties of cultivars that differ from those
192 grown in field experiments. For example, the field experiment in Wageningen (The
193 Netherlands) indicated a large negative impact of temperature rise on wheat yield (-
194 11.6% per °C) but used a spring wheat that is not representative of the region (15).
195 Positive impacts ($11.2 \pm 1.2\%$ per °C) were observed in wheat warming experiments in

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

201

202 We assumed the temperature response of impact on yield would be linear and
203 multiplied projected temperature changes (Fig. 1B) with our multi-method impact
204 estimates to give an average projected decrease in the global crop yields of 5.6% (95%
205 CI, 0.1-14.4%) due to temperature change alone under the scenario of lowest emissions
206 (RCP2.6) going up to 18.2% (95% CI, 0.7-38.6%) under the scenario of highest
207 emissions (RCP8.5) (Fig. 2B). The estimated responses in yield are primarily from
208 around +2 °C warming simulations, regressions and experiments (see Methods), so the
209 estimates of impact for a global warming scenario near +4 °C (RCP8.5) are likely to be
210 conservative due to the non-linear impact of rising temperatures in the real world (4,
211 18). A non-linear response to temperature has also been suggested in simulations (1, 7,
212 10).

213

214 To prepare for adaptation to climate change, it is necessary to isolate the effects of
215 individual factor for possible impacts on yield, as changes in different factors usually
216 require different adaptation strategies. While elevated atmospheric CO₂ concentration
217 can stimulate growth when nutrients are not limited, it will also increase canopy
218 temperature from more closed stomata (19). Also changes in precipitation can have an
219 effect on crops, but projections on precipitation change are often uncertain. The focus of

220 our study is on temperature change, one of the most direct negative impact from climate
221 change on crops, and does not include other possible climate change effects from
222 elevated atmospheric CO₂ concentration or changes in rainfall, and possible deliberate
223 adaptation taken by farmers. Farmers have increased yields through adapting new
224 technologies during the last half century, but yield has been also lost through increases
225 in temperatures already (8). Yield increase has slowed down or even stagnated during
226 last years in some parts of the world (20, 21) and further increases in temperature will
227 result in further decreases in observed yields, in spite of farmers' adaptation efforts.

228

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

240

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

244 However, differences in temperature responses of crops around the world suggest some
245 mitigation could be possible to substantially affect the magnitude (or even direction) of
246 climate change impacts on agriculture. These impacts will also vary substantially for
247 crops and regions, and may interact with changes in precipitation and CO₂, so a
248 reinvigoration of national research and extension programs is urgently needed to offset
249 future impacts of climate change, including temperature increase on agriculture using
250 crop- and region-specific adaptation strategies.

251

252 **Materials and Methods**

253 **Temperature data**

254 Historical observed gridded monthly temperature data are from the Climate
255 Research Unit (0.5° × 0.5° grid, CRU TS 3.23;
256 <https://crudata.uea.ac.uk/cru/data/temperature/>). Future predicted temperature data are
257 from the Coupled Model Intercomparison Project Phase 5 (CMIP5) Earth System
258 Models (ESMs) outputs (1.0° × 1.0° grids; <http://cmip-pcmdi.llnl.gov/cmip5>) used in the
259 IPCC AR5 (28). According to data availability, the outputs from 15, 20, 11 and 22
260 ESMs were included in this study for RCP2.6, RCP4.5, RCP6.0 and RCP8.5 scenarios,
261 respectively. However, the calculated temperature changes are very similar to those
262 calculated using all the ESMs (IPCC 5). The annual mean temperature over the global
263 growing area of an individual crop was calculated by weighting each grid cell average
264 (0.5° × 0.5° grids) according to the crop growing area within the grid cell (29).

265

266 **Global gridded crop model simulations**

267 The Agricultural Model Intercomparison and Improvement Project (AgMIP) (30)

268 and Inter-Sectoral Impact Model Intercomparison Project 1 (ISI-MIP-1) (31) initiated a
269 fast-track global climate impact assessment for the main global crops in 2012, including
270 wheat, rice, maize and soybean. Seven global gridded crop models were used to
271 simulate crop yield in $0.5^\circ \times 0.5^\circ$ grid cells over the globe, forced with climate
272 reconstruction for 1980-2099 based on HadGEM2-ES (32) derived from CMIP5. The
273 simulations were carried out under a scenario of constant CO₂ concentration (380 ppm
274 in 2000) and full irrigation, to exclude the possibility of covariance with CO₂ and
275 precipitation. More detailed information about the simulations can be found in (1, 33).
276 Temperature impact values were calculated from yield changes between 2029-2058 (+2
277 °C of global mean temperature) and 1981-2010 (baseline) which were then halved to
278 give +1 °C of global temperature impact. For global or country results, all the grids were
279 averaged by weighting the corresponding growing area of each crop (29).

280

281 **Point-based ensemble simulations**

282 The Agricultural Model Intercomparison and Improvement Project (AgMIP) (30)
283 also conducted crop yield simulations at 30, 4 and 4 representative sites around the
284 world (Fig. S1) by using 30 wheat, 13 rice and 19 maize models, respectively. For
285 wheat, a scenario of +2 °C was created by adjusting each day's temperature by +2 °C
286 relative to the baseline (1981-2010), other factors being constant. For rice and maize,
287 the +3 °C scenarios were used. Model details about simulations for each crop can be
288 found in refs 7, 11 and 12. The temperature impact was calculated as the yield change
289 during the warming period relative to the yield during the baseline period normalized to
290 +1 °C impact, assuming impact showed a linear temperature response. To obtain values
291 for impacts at the country scale, each country was deemed to be similar to one or more

292 representative sites located in said (or nearby) country. As local temperature change can
293 be different to the country mean, the local point-based estimates were scaled up by
294 multiplying each country's temperature factor produced by HagGEM2-ES (28), as in ref.
295 7. The weighted average temperature impacts over all the countries were used to
296 estimate the globe scale impact, weighted by country-level production (14). It should be
297 noted that the results from only 4 sites were used to represent all the rice/maize-
298 producing countries, which might not encompass all the uncertainties from diverse
299 production systems and is also one limitation in our analysis. No point-based model-
300 ensemble simulations for soybean were conducted in AgMIP.

301

302 **Field-warming experiments**

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

316

317 **Statistical regressions**

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

333

334 **Multi-method ensemble**

335 The above four methods constituted the method ensemble that we used to estimate
336 multi-method means and uncertainties. In this study, values from the method ensembles
337 were synthesized at site, country and global scale. At the country scale, the temperature
338 impacts from regression methods were only reported for the five countries producing
339 each crop, thus the results mainly focus on the relevant top five countries. The

340 uncertainty for the method ensemble was calculated by using a formula: $\text{var}(Y) =$
341 $\text{var}(E(Y|\text{method})) + E(\text{var}(Y|\text{method}))$, where the term $(\text{var}(E(Y|\text{method})))$ is a measure
342 of the variability between methods, and $E(\text{var}(Y|\text{method}))$ is a measure of the average
343 variability within methods, assuming that this is random sample of approaches from a
344 population of approaches. Confidential intervals (CI) at 95% were calculated for the
345 multi-method mean as: 95% CI = mean of methods $\pm 1.96 \times \sqrt{\text{var}(Y)}$.

346

347 **Comparisons between methods**

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

364

365 **Prediction of yield changes by the end of century**

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

377

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394 **Footnotes**

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403 The authors declare no competing financial interests.

404

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485

486 **Figure legends**

487 **Figure 1. Mean annual temperature changes over time.** (A) Historically observed
488 temperature anomalies relative to 1961-1990 for global growing areas of four individual
489 crops. (B) Future projected temperature changes (2071–2100 in comparison to 1981–
490 2010 baseline) of four crop-growing areas and the globe (land and sea surface) under
491 four representative concentration pathway (RCP) scenarios of increasing greenhouse
492 gas concentrations. Error bars represent standard deviations in the climate model results.

493

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

503

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

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

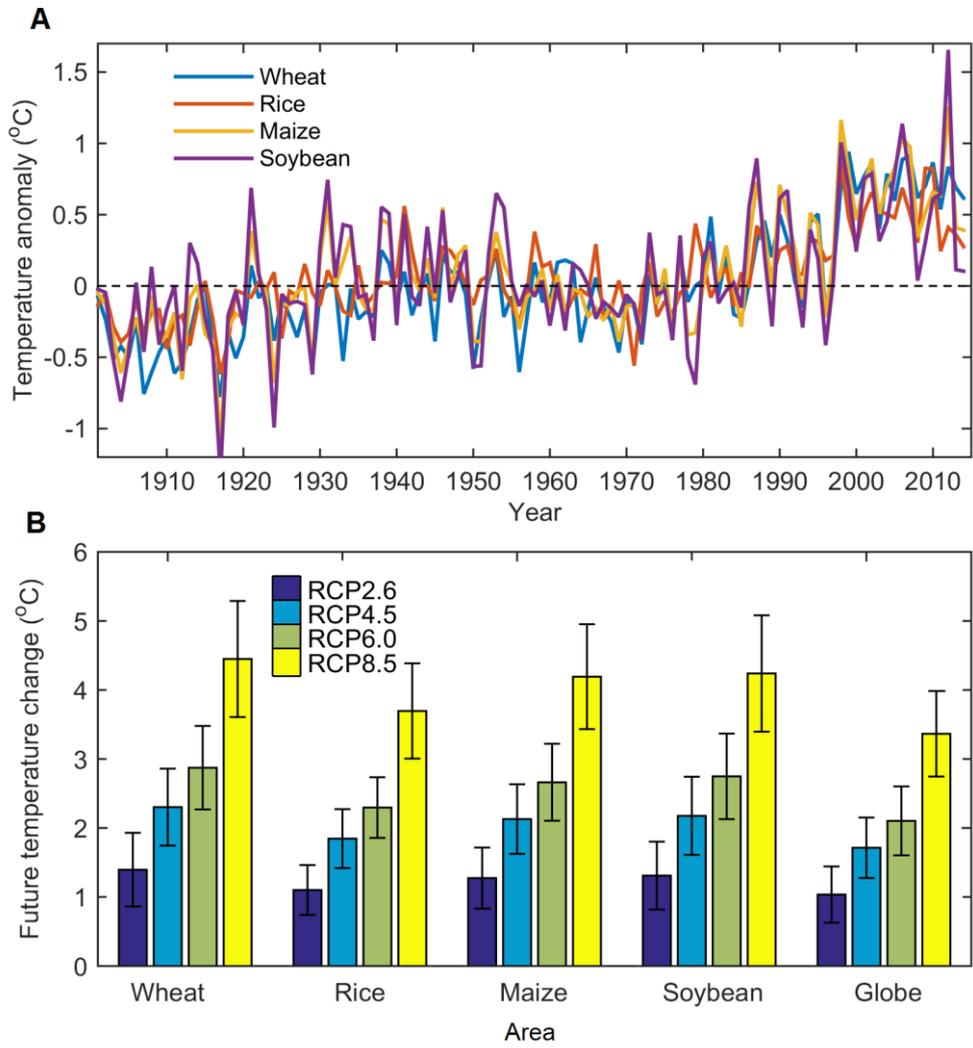
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515 **Figure 4. Site-based multi-method ensemble of crop yield changes with 1 °C of**
516 **global temperature increase.** Site estimates from >3 methods are shown for (A) wheat,
517 (B) rice and (C) maize or from 2 methods for (D) soybean. Grid-Sim,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

523

524 **Figure 1**

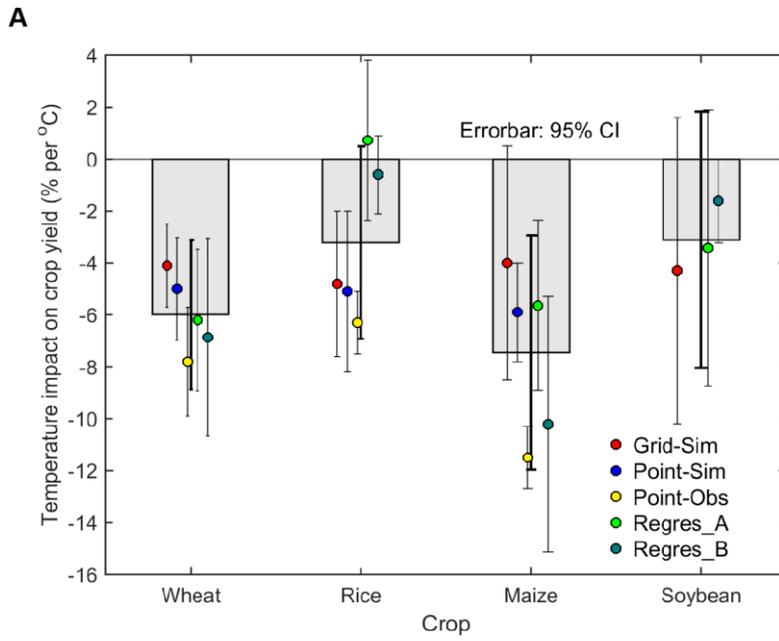
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527 **Figure 2**

528



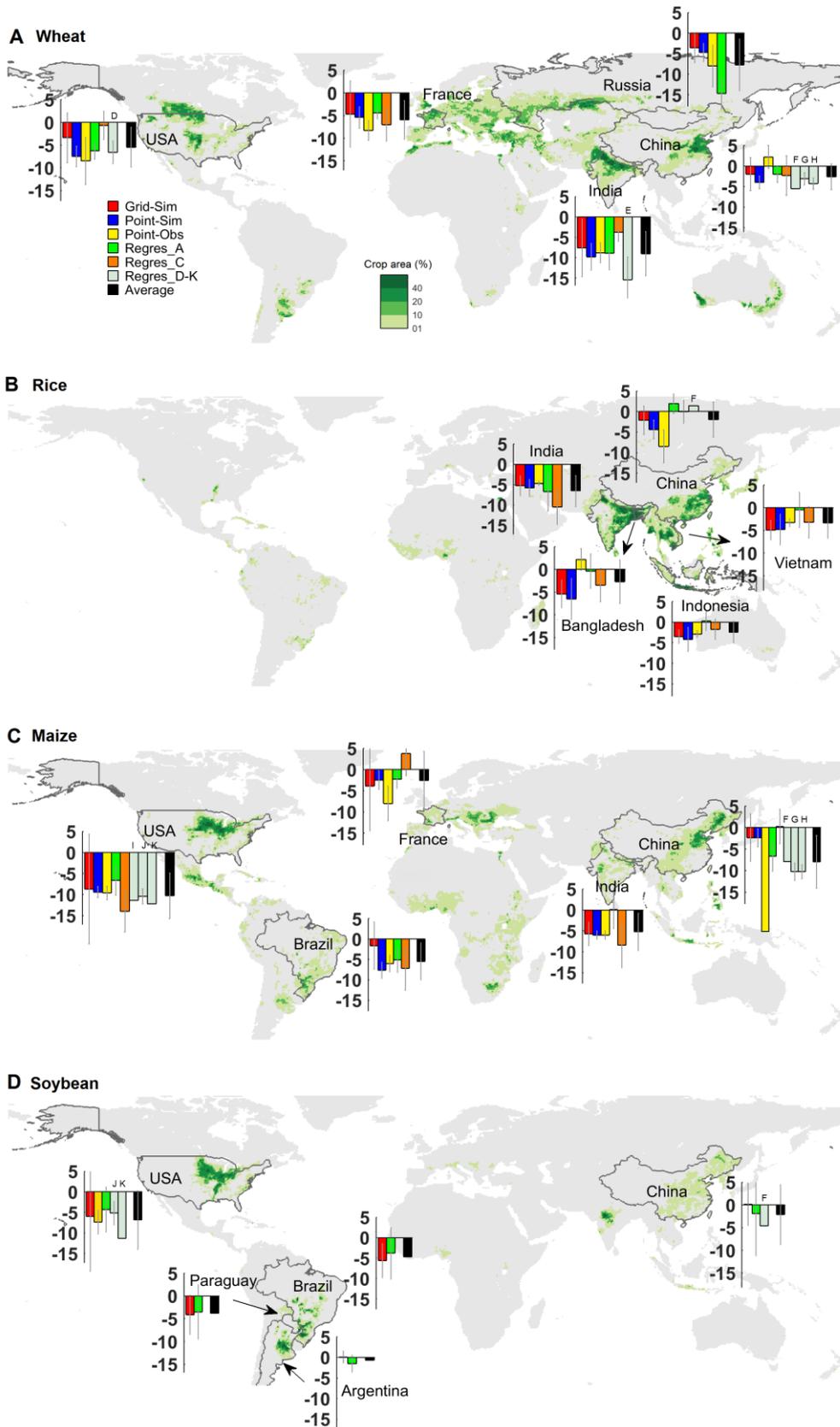
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Scenario	Yield changes (%) due to temperature changes by the end of century				
	Wheat	Rice	Maize	Soybean	Mean
RCP2.6	-6.9	-3.3	-8.6	-3.6	-5.6
	[-15.0, -1.4]	[-9.2, 0.8]	[-18.6, -1.8]	[-11.2, 1.7]	[-14.4, -0.1]
RCP4.5	-11.4	-5.5	-14.2	-5.9	-9.2
	[-21.7,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

529

530 **Figure 3**

531



532

533 **Figure 4**

534

