

The impact of future warming on global rice yield

Chuang Zhao¹, Shilong Piao^{1,2,3}, Xuhui Wang¹, Yao Huang⁴, Philippe Ciais⁵, Joshua Elliott⁶, Mengtian Huang¹, Ivan A Janssens⁷, Tao Li⁸, Xu Lian¹, Yongwen Liu¹, Christoph Müller⁹, Shushi Peng¹, Tao Wang^{2,3}, Zhenzhong Zeng¹, Josep Peñuelas^{10,11}

¹ Sino-French Institute for Earth System Science, College of Urban and Environmental Sciences, Peking University, Beijing 100871, China

² Key Laboratory of Alpine Ecology and Biodiversity, Institute of Tibetan Plateau Research, Chinese Academy of Sciences, Beijing 100085, China

³ Center for Excellence in Tibetan Earth Science, Chinese Academy of Sciences, Beijing 100085, China

⁴ State Key Laboratory of Vegetation and Environmental Change, Institute of Botany, Chinese Academy of Sciences, Beijing 100093, China

⁵ Laboratoire des Sciences du Climat et de l'Environnement, CEA CNRS UVSQ, Gif-sur-Yvette, France

⁶ University of Chicago Computation Institute, Chicago, IL 60637, United States of America

⁷ Department of Biology, University of Antwerp, Universiteitsplein 1, 2610 Wilrijk, Belgium

⁸ International Rice Research Institute, Los Baños, Philippines

⁹ Potsdam Institute for Climate Impact Research, 14473 Potsdam, Germany ¹⁰ CREAM, Cerdanyola del Valles, Barcelona 08193, Catalonia, Spain.

¹¹ CSIC, Global Ecology Unit CREAM-CEAB-CSIC-UAB, Cerdanyola del Valles,

Post-print of: Zhao, Ch., et al. "Plausible rice yield losses under future climate warming" in *Nature plants* (Ed. Nature), vol. 3 (Des. 2016) art. 16202. The final version is available at DOI 10.1038/nplants.2016.202

24 Barcelona 08193, Catalonia, Spain.

25 **Manuscript for *Nature Plants***

26

27

28 **Rice is the staple food for more than 50% of the world's population¹⁻³. Reliable**

29 **prediction of changes in rice yield is thus central for maintaining global food security.**

30 **Here, we compare the sensitivity of rice yield to temperature increase derived from**

31 **field warming experiments and three modelling approaches: statistical models, local**

32 **crop models and global gridded crop models. Field warming experiments produced**

33 **a substantial rice yield loss under warming, with an average temperature sensitivity**

34 **of $-5.2 \pm 1.4\% \text{ K}^{-1}$. Local crop models gave a similar sensitivity ($-6.3 \pm 0.4\% \text{ K}^{-1}$), but**

35 **statistical and global gridded crop models both suggest less negative impacts of**

36 **warming on yields ($0.8 \pm 0.3\% \text{ K}^{-1}$ and $-2.4 \pm 3.7\% \text{ K}^{-1}$, respectively). Using data from**

37 **field warming experiments, we further propose a conditional probability approach**

38 **to constrain the large range of global gridded crop model results for the changes in**

39 **future yield in response to warming by the end of the century (from $-1.3\% \text{ K}^{-1}$ to -**

40 **$9.3\% \text{ K}^{-1}$). The constraint implies a more negative response to warming ($-8.3 \pm 1.4\%$**

41 **K^{-1}) and reduces the spread of the model ensemble by 35%. This yield reduction**

42 **exceeds that estimated by the International Food Policy Research Institute**

43 **assessment (-4.2 to $-6.4\% \text{ K}^{-1}$)⁴. Our study suggests that without CO₂ fertilization,**

44 **effective adaptation and genetic improvement, severe rice yield losses are plausible**
45 **under intensive climate warming scenarios.**

46

47 Hunger and malnutrition are two alarming problems calling for increased yields^{5,6}.
48 Rice is currently one of the most widely grown crops in the world and the main source
49 of calories in developing countries¹⁻³. Any reduction in rice productivity could,
50 therefore, have dramatic implications for global food security⁵. Climate warming
51 exceeding the optimum physiological temperature of rice plants has been shown to
52 cause such a reduction^{7,8}. The assessment of food security from the International Food
53 Policy Research Institute (IFPRI) also stated that climate change, without the separate
54 effects of CO₂ fertilization, would cause a 10-12% reduction of irrigated rice yield
55 globally by 2050⁴. Unfortunately, we have poor understanding of the physiological
56 mechanisms through which rice plants may respond to climate change. Many studies
57 are using process-based crop models to project climate change impacts on crop yields⁹⁻
58 ¹⁰. These models integrate plant-scale physiological mechanisms, and can be run at site,
59 regional or global scale with forcing variables derived from global climate models under
60 different greenhouse gas emission scenarios. Yet, the parameters of crop models are
61 usually not measured across the full scale of model applications, and model equations

62 may also be wrong, leading to large uncertainties in projections of future climate change
63 impacts¹⁰⁻¹².

64

65 The Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP-1)¹³ and the
66 Agricultural Model Intercomparison and Improvement Project (AgMIP)¹⁴ coordinated
67 multi-model simulations of the yields of major crops, including rice. One of the findings
68 of AgMIP is that multi-model mean or median values give better simulations of the
69 observed yield of rice¹⁵ than any individual model, but it remains unclear whether the
70 ‘average model’ is meaningful at all. Errors in parameter values, as well as in model
71 structure, result in large model-to-model variation in simulated yield¹⁰. However, if the
72 bias of a model for the present persists into the future, an emerging constraint can be
73 established through which present-day observations can be used for eliminating less
74 realistic models in the simulation of temperature response; this reduces the uncertainty
75 in the ensemble projection. This heuristic approach called ‘emerging constraint’ has
76 been applied to constrain simulations, e.g., of the sensitivity of the tropical carbon cycle
77 and of snow albedo, to temperature^{16,17}. Here, to reduce the large range of the ISI-MIP1
78 global gridded crop models (GGCMs)¹⁸ for the sensitivity of rice yield to temperature,
79 we use a new compilation of data from 83 field warming experiments at 13 sites over
80 the globe (Supplementary Table 1) (see Methods).

81

82 Five GGCMs driven by daily weather outputs from five climate models (CM) (see
83 Methods) were run under the high warming Representative Concentration Pathway
84 RCP8.5 (2070-2099) scenario, with CO₂ fixed at the present-day value (excluding the
85 relevant benefits from CO₂ fertilization in the future). This procedure allows us to
86 estimate the effect of climate change alone on yield. The five climate models used to
87 drive the GGCMs, gave an increase in growing-season mean air temperature over
88 ricegrowing areas ranging from 3.3 K (GFDL-ESM2M) to 5.0 K (IPSL-CM5A-LR)
89 relative to today (Fig. 1a). The median value of the climate-induced rice yield change
90 was -27% (Fig. 1b) — a large yield reduction which would pose a threat to future food
91 security. However, the range of model responses was large, reflecting uncertainties in
92 climate projections and in GGCMs, with yield reductions ranging from 6.6% in
93 LPJGUESS+HadGEM2-ES to 42.4% in EPIC+HadGEM2-ES (see also ref.18).
94 Dividing the changes in yield by the magnitude of temperature warming above present-
95 day values defines the long-term sensitivity of rice yield to warming by the end of the
96 twenty-first century (). This sensitivity was negative for all combinations of GGCM
97 and climate model, and ranged from -1.3% K⁻¹ with LPJ-GUESS+HadGEM2-ES to -
98 9.3% K⁻¹ with EPIC+HadGEM2-ES; the median value was -6.5% K⁻¹.

100 Then, for each GGCM-CM pair, we also calculated the present-day interannual
101 temperature sensitivity of rice yield () for the model grid cells where the field
102 experiments were located, using multiple linear regression models to separate the
103 sensitivity of modelled yields (1971-2000) to growing-season temperature, precipitation
104 and radiation. Figure 2a shows that there is an emerging strong linear relationship
105 ($R^2=0.75$, $P<0.001$) between long-term () and present-day interannual () sensitivities
106 of yield to temperature across all GGCM-CM combinations. This means that a model
107 showing a high negative yield response to warm years during the last 30 years also
108 projects a high warming-induced yield decrease in the future. This implies that the
109 GGCM responses to temperature are generally conserved between historical and future
110 conditions.

111

112 To assess the realism of these modelled yield sensitivities to warming, we compiled
113 data from field experiments where rice plots were warmed (Supplementary Table 1).
114 More than 80% (67 out of 83) of the field experiments reported a rice yield loss under
115 warming, with an average observed sensitivity of yield to warming () of $-5.2\pm 1.4\%$ K⁻¹
116 (Fig. 3). According to the ‘emerging constraint’ method (see Methods), these field
117 experiments provided an observation-based probability density function (PDF) for

118 modelled β , and the linear relationship between β and ΔT (Fig. 2a) provided another PDF of
119 β , for a given ΔT . The conditional probability of modelled
120 β , that is consistent with the PDF of observed sensitivities (red dashed line in Fig.
121 2b) gives a PDF of constrained modelled β . The maximum likelihood value of this
122 constrained β sensitivity was more negative ($-8.3 \pm 1.4\% \text{ K}^{-1}$) than the one of the original
123 model ensemble (Fig. 2b), and the 1-sigma uncertainty of the PDF of β was reduced
124 by 35%. This means that the information from field warming experiments shifts the
125 modelled long-term temperature sensitivities of rice yield towards more negative
126 values, and reduces the variation among models. When applying the same emerging
127 constraint of the conditional probability to the model grid cells of the experimental sites,
128 or to the grid cells with similar climate or similar rice yield, the constrained β values in
129 all cases were more negative than the original ensemble of models, and had a lower
130 uncertainty (Supplementary Fig. 1).

131

132 The temperature sensitivities obtained from field experiments can also be
133 considered as realistic analogues of GGCM long-term sensitivities, because both
134 approaches consider a warming over ambient conditions of similar magnitude.
135 Replacing the present-day temperature sensitivities (β) over the GGCM grid cells of

136 experimental sites (horizontal-axis variable) with that of the long-term ones () in Fig.
137 2, we found that the experimentally constrained , was $-7.2 \pm 1.5\% \text{ K}^{-1}$, still less uncertain
138 and more negative than the unconstrained value reflecting the spread of all the GGCMs
139 forced by different climate models (Supplementary Fig. 2).

140

141 With the emerging constraint approach of this study, it is important to assess all the
142 uncertainties that might bias the final result. For instance, some experiments included
143 multiple warming treatments and nutrient levels. We thus verified that , depends neither
144 on the magnitude of warming applied (Supplementary Fig. 3, $P > 0.1$), nor on the
145 background growing-season temperature (Supplementary Fig. 4, $P > 0.1$) or nutrient
146 levels (Supplementary Fig. 5, $P > 0.1$) across the set of experiments we have compiled.

147 In addition, field experiments had different designs and used different techniques to
148 warm the plots. Passive warming techniques using greenhouses or open-top-chambers
149 were criticized because they also alter light, wind, and soil moisture^{19,20}—active
150 warming techniques using artificial heaters are considered more reliable^{20,21}. When only
151 the results from active warming experiments were used (Supplementary Fig. 6), the
152 constrained , was $-7.0 \pm 1.7\% \text{ K}^{-1}$, remaining more negative than the unconstrained value,
153 but the uncertainty reduction achieved for model results was smaller (only 19% against
154 35% with all experiments), which is attributed mainly to the small number of active
155 warming experiments published so far (only five sites; Supplementary Table 1).

156

157 A second source of uncertainty in our approach is that the values of β , derived from
158 model simulations represent the average yield change divided by the average
159 temperature increase averaged over many years with non-uniform warming across the
160 growing season, whereas field experiments last only a few years. Using individual
161 years, instead of the average of the last 30 years of the twenty-first century, to calculate
162 β , the constrained β , remained less uncertain and more negative than the unconstrained
163 value for 29 individual years (Supplementary Fig. 7). Our result is thus robust and not
164 sensitive to the method used to define the long-term yield sensitivity to warming in
165 model outputs. In addition, warming experiments located in the US (24 out of 83
166 experiments, Supplementary Table 1) might be not representative of the varieties,
167 edaphic and climate conditions over today's dominant rice growing regions in Asia.
168 However, even when using only the experiments performed on Asian rice varieties, with
169 only the GCM grid cells of these regions, the emerging linear relationship between β ,
170 and ΔT , was still present (Supplementary Fig. 8, $R^2=0.74$, $P<0.001$), and the constrained β ,
171 was $-6.9\pm 1.4\% \text{ K}^{-1}$, less uncertain than the unconstrained value ($-5.8\pm 2.0\% \text{ K}^{-1}$).

172

173 Why does the ISI-MIP-1 ensemble median of pairs of GGCMs and climate models
174 underestimate rice yield losses in response to warming (Fig. 2b)? One reason might be
175 the inclusion of adaptation in some GGCMs. For instance, LPJ-GUESS assumes very
176 flexible adaptation in growing-season lengths, i.e., plasticity of cultivars, and GEPIC
177 allows for adaptation in sowing dates. Removing these two models from the constraint,
178 does not remove this underestimation (Supplementary Fig. 9), suggesting that the fact
179 that some models include a degree of adaptation does not eliminate the underestimated
180 , in GGCMs. Also, the use of CM-based climate scenarios with non-uniform warming
181 across the growing season and where also changes in radiation and precipitation are
182 included, can lead to a veiled temperature response. As most of the rice production is
183 fully irrigated, we assume that the temperature signal is the dominant climate impact
184 also in the CM-driven GGCM simulations. Another reason could be that the ensemble
185 did not contain a sufficiently large enough number of crop models (five in our study).
186 All the possibilities of current rice models may not have been included and this would
187 hamper the strength of the model ensemble^{10,15}. Fortunately, a larger number of crop
188 models will be used in the Phase II of ISI-MIP/AgMIP; this will allow a further test of
189 the robustness of the emerging constraint approach.

190

191 Independently from field warming experiments and GGCMs, there are also a large
192 number of publications from local crop models used to interpret field trials (arguably

193 those models are well calibrated to specific rice varieties and cultivation practice) and
194 from statistical models where the sensitivity of rice yield to temperature change is
195 derived from observed interannual variability. These different temperature sensitivities
196 are shown in Fig. 3 for the present-day period and the future (end of the century). For
197 the present-day sensitivities, 95% of local crop model simulations (329 studies out of
198 346) give a negative response to warming, with a mean sensitivity of $-6.3 \pm 0.4\% \text{ K}^{-1}$,
199 more negative but consistent with the values inferred from field warming experiments
200 ($-5.2 \pm 1.4\% \text{ K}^{-1}$). Statistical models have a surprisingly lower percentage of studies (46
201 studies out of 77) presenting negative , than warming experiments (more than 80% of
202 studies), and also give a weaker mean sensitivity (, $-0.8 \pm 0.3\% \text{ K}^{-1}$; Fig. 3) than both
203 warming experiments and local crop models. This weak sensitivity might be due to the
204 aggregated nature and disputable quality of historical yield and weather data in different
205 regions²², to difficulties in separating the temperature effect from co-varying
206 management practice²³, increasing CO₂, and to non-linearity in the temperature
207 response²⁴. Lower sensitivities are also found in the GGCM results during the
208 presentday period compared to the long term (Fig. 3). This suggests that GGCMs have
209 thresholds above which the temperature response of rice yield becomes significantly
210 more negative (see also ref. 18).

211

212 We also compared our , value with that implied from IFPRI (as a
213 representative of the policy community) who project the future of the world's food
214 supply. They predicted 10 and 12% losses of global rice yield by 2050, based on
215 temperature increase scenarios of 1.5 °C and 2.9 °C, respectively⁴. Thus a rough
216 estimate of the sensitivity of rice yield to warming is -4.2 to -6.4% K⁻¹, a smaller
217 magnitude than that from the global crop models constrained by experimental data in
218 our study (-8.3±1.4% K⁻¹). However, we noted that the constrained , derived here was
219 for the end of this century (2070-2099), inconsistent with the time frame used by IFPRI
220 (2050s). When applying the emerging constraint to the time frame of midcentury (2036-
221 2065), the constrained , was -8.5±2.3% K⁻¹ (Supplementary Fig. 10) — still a larger
222 magnitude than the number from IFPRI. This result suggests that warming appears to
223 present an even greater challenge to rice than expected and more effective adaptation
224 strategies are thus required.

225

226 The prediction of yield loss under future warming notably does not consider
227 otherthan-climate factors that could sustain or increase yield, in particular increased
228 CO₂^{25,26},

229 adaptation^{11,27} and improved management/cultivars that are independent of adaptation

230 to warmer temperatures²⁸. For instance, the current rates of genetic gains in yield for

231 hybrid rice are 0.6-0.7% yr⁻¹ ²⁸. In our study, the results from the global gridded crop
232 model constrained by observations suggest a yield loss of 37% for the end of the century
233 due to increased temperature under the RCP8.5 scenario (multiply the constrained
234 sensitivity in Fig. 2 by climate warming in Fig. 1), but the loss will unfold over 70 years,
235 i.e., at an average rate of 0.5% yr⁻¹. The genetic improvement sustained during one
236 century at current rates could thus offset the negative impact from increased
237 temperature. To fulfil the projected increase in cereal demand for the world population
238 (~1.2% yr⁻¹)²⁹, however, the increase in rice yield from technological change, together
239 with the CO₂ effect and adaptation, would need to be much higher (1.7% yr⁻¹) to offset
240 the development of negative effects of climate change at a rate of 0.5% yr⁻¹.

241

242 Our study, combining field warming experiments with three modelling approaches,
243 comprehensively assessed the global response of rice yield to warming. The main result
244 is that all approaches indicated a decrease in rice yield in response to warming, and the
245 field warming experiments suggested an even higher risk of future yield reductions than
246 that inferred from unconstrained GGCM results. Future experiments with standard
247 measurement protocols, long time periods and a large range of rice genotypes and
248 management types³⁰ should provide more insight on constraining modelling results. Our

249 results, however, show that warming under climate change poses a significant threat to
250 rice production and thus to a major staple food with substantial impact on the food
251 security of developing and emerging economies. The long-term perspective of climate
252 change allows us to prepare agricultural production systems for this challenge, but
253 suitable policies must be put in place in the near future, given that targeted research on
254 adaptation options and their large-scale implementation will require considerable time.

255

256 **Methods**

257 **ISI-MIP data set.** Starting in 2012, the Inter-Sectoral Impact Model Intercomparison
258 Project (ISI-MIP-Phase 1 project; *isi-mip.org*) used multi-model ensembles to assess
259 the climate change impacts across multiple sectors. In the agriculture sector, multiple
260 global gridded crop models (GGCMs)¹⁸ were used to simulate crop yield. We used yield
261 simulated by five GGCMs (EPIC, GEPIC, LPJ-GUESS, LPJmL and pDSSAT). These
262 model outputs are available as annual time series at a spatial resolution of 0.5×0.5
263 degrees. GGCM simulations were driven by historical (1971–2005) and future (2006–
264 2099) climate forcing including temperature, precipitation and solar radiation. These
265 forcing data were taken from a bias-corrected climate data set based on five climate
266 models (CMs) in the Coupled Model Intercomparison Project Phase 5 (CMIP5)³¹. Of
267 the ISI-MIP crop model ensemble, PEGASUS did not provide yield data for rice and
268 GAEZ-IMAGE was excluded because its modelling approach does not provide

269 sufficient information on interannual variability to calculate the temperature sensitivity
270 of rice yield. More detailed information about the five GGCMs which were used can be
271 found in ref.18. The high-emission scenario, representative concentration pathway
272 (RCP) 8.5 was chosen as it not only represents the upper end of projected climate
273 change, but also provides the largest ensemble of GGCM-CM combinations to consider
274 the broadest possible range of climate impacts. GEPIC and LPJ-GUESS only
275 contributed data for one CM (i.e., HadGEM2-ES) and thus a total of seventeen
276 GGCMCM combinations were used in our analysis. All GGCM-CM simulations used
277 here were conducted with constant CO₂ concentration and current management (see ref.
278 18 for exceptions). We used the model output for the full irrigation scenario, since
279 irrigated rice currently makes up about 75% of world production³.

280

281 **Literature review.** We searched peer-reviewed and primary research from Web of
282 Science, Google Scholar and China National Knowledge Infrastructure (CNKI,
283 <http://www.cnki.net>) that was published before January 2015. All publications related
284 to the responses of rice yield to temperature change were considered. Three main
285 approaches were distinguished, namely, local process-based crop models, statistical
286 models and field warming experiments. To obtain the sensitivity of rice yield to

287 temperature (°C; yield change per K), local process-based models usually conduct an
 288 arbitrary sensitivity test (e.g., +2 °C scenario), with other conditions kept constant;
 289 whereas statistical models use regression equations to relate historical records of rice
 290 yield to weather including temperature. On the other hand, field warming experiments
 291 apply direct warming treatments to rice in field plots. μ is calculated as :

$$292 \quad \mu = \Delta Y / \Delta T \quad (1)$$

293 where ΔY and ΔT are the rice yield change and temperature change, respectively. The
 294 average μ , and its uncertainty for experiments are obtained from bootstrap resampling.

295 Here we assume the experimental data (Supplementary Table 1) as: $X = \{X_1, X_2, \dots, X_n\}$,

296 where X_n represent all the experiments at site n . The steps of bootstrapping are as

297 follows: (1), resample one experiment at each site to obtain a bootstrap resample: $X_1^* =$

298 (x_1, x_2, \dots, x_n) , where x_n represent the sampled experiment at site n . (2), compute the

299 mean of this resample and obtain the first bootstrap mean: $\mu_1^* = \frac{1}{n} \sum$. (3), repeat the

300 process of (1) and (2) to obtain the second resample X_2^* and compute the second

301 bootstrap mean μ_2^* . Repeating this 5000 times, we have $\mu_1^*, \mu_2^*, \dots, \mu_{5000}^*$, which

302 constitute an empirical bootstrap distribution of sample mean. Here each μ^* represents

303 one case of average sensitivity for all the sites (Supplementary Fig. 11). The difference

304 between μ^* values is from the use of different experiment within sites. Therefore, the

305 PDF now reflects the variations caused by different experiments within sites.

306

307

308 **Constraint.** Our constraint methodology comes from Cox *et al.*¹⁶, who built an
309 emergent linear relationship between the sensitivity of tropical land-carbon storage to
310 warming and the sensitivity of the annual growth rate of atmospheric CO₂ to tropical
311 temperature anomalies across models. They then used the historical observed CO₂
312 growth rate sensitivity to temperature to constrain the uncertainties of future climate
313 impact on tropical carbon through the conditional probability approach. Here we used
314 a similar approach, first building the relationship between the historical temperature
315 sensitivity of crop yield and the future yield feedbacks across the GGCM
316 modelensembles, and then using the observed field warming experiments to constrain
317 future modelled yield-climate feedbacks. The details of the constraint methods are
318 described in Supplementary Methods. It should be noted that the PDF of GGCM-CM
319 could be biased, because some crop models (GEPIC and LPJ-GUESS) were only paired
320 with one CM (HadGEM2-ES). This unbalance in the selection of the GGCM-CM
321 combination was checked with five GGCMs but with random selection of different
322 CMs, i.e., one pair of GGCM-CMs with random CM selection (Supplementary Fig. 12).

323

324 **References**

- 325 1. FAOSTAT, <http://faostat.fao.org/default.aspx> (2014).
- 326 2. Seck, P. A., Diagne, A., Mohanty, S. & Wopereis M. C. Crops that feed the world
327 7: rice. *Food Secur.* **4**, 7–24 (2012).
- 328 3. Maclean, J. L., Dawe, D. C., Hardy, B. & Hettel, G. P. Eds., *Rice Almanac* (CABI
329 Publishing, Wallingford, UK, 2002), pp.18.
- 330 4. Nelson, G. C. *et al.* Food security, farming, and climate change to 2050: Scenarios,
331 results, policy options. *Int. Food Policy Res. Inst.* **172** (2010).
- 332 5. Godfray, H. C. *et al.* Food security: The challenge of feeding 9 billion people.
333 *Science* **327**, 812–818 (2010).
- 334 6. Foley, J. A. *et al.* Solutions for a cultivated planet. *Nature* **478**, 337–342 (2011).
- 335 7. Gourdj, S. M., Sibley, A. M. & Lobell, D. B. Global crop exposure to critical high
336 temperatures in the reproductive period: historical trends and future
337 projections. *Environ. Res. Lett.* **8**, 024041 (2013).
- 338 8. Sánchez, B., Rasmussen, A. & Porter, J. R. Temperatures and the growth and
339 development of maize and rice: a review. *Global Change Biol.* **20**, 408–417 (2014).
- 340 9. Rosenzweig, C. & Parry, M. L. Potential impact of climate change on world food
341 supply. *Nature* **367**, 133–138 (1994).
- 342 10. Asseng, S. *et al.* Uncertainty in simulating wheat yield under climate change. *Nature*
343 *Clim. Change* **3**, 827–832 (2013).

- 344 11. Challinor, A. J. *et al.* A meta-analysis of crop yield under climate change and
345 adaptation. *Nature Clim. Change* **4**, 287–291 (2014).
- 346 12. Rötter, R. P., Carter, T. R., & Olesen, J. E. Crop–climate models need an overhaul.
347 *Nature Clim. Change* **1**, 175–177 (2011).
- 348 13. Warszawski, L. *et al.* The Inter-Sectoral Impact Model Intercomparison Project
349 (ISI–MIP): Project framework. *Proc. Natl. Acad. Sci. U.S.A.* **111**, 3228–3232
350 (2014).
- 351 14. Rosenzweig, C. *et al.* The agricultural model intercomparison and improvement
352 project (AgMIP): protocols and pilot studies. *Agric. For. Meteorol.* **170**, 166–182
353 (2013).
- 354 15. Li, T. *et al.* Uncertainties in predicting rice yield by current crop models under a
355 wide range of climatic conditions. *Global Change Biol.* **21**, 1328–1341 (2015).
- 356 16. Cox, P. M. *et al.* Sensitivity of tropical carbon to climate change constrained by
357 carbon dioxide variability. *Nature* **494**, 341–344 (2013).
- 358 17. Hall, A. & Qu, X. Using the current seasonal cycle to constrain snow albedo
359 feedback in future climate change. *Geophys. Res. Lett.* **33**, L03502,
360 doi:10.1029/2005GL025127 (2006).

- 361 18. Rosenzweig, C. *et al.* Assessing agricultural risks of climate change in the 21st
362 century in a global gridded crop model intercomparison. *Proc. Natl. Acad. Sci.*
363 *U.S.A.* **111**, 3268–3273 (2014).
- 364 19. Kimball, B. A. Theory and performance of an infrared heater for ecosystem
365 warming. *Global Change Biol.* **11**, 2041–2056 (2005).
- 366 20. Aronson, E. L. & McNulty, S. G. Appropriate experimental ecosystem warming
367 methods by ecosystem, objective, and practicality. *Agric. For. Meteorol.* **149**, 1791–
368 1799 (2009).
- 369 21. De Boeck, H. J. & Nijs, I. An alternative approach for infrared heater control in
370 warming and extreme event experiments in terrestrial ecosystems. *J. Ecol.* **99**, 724–
371 728 (2011).
- 372 22. Lobell, D. B. *et al.* Prioritizing climate change adaptation needs for food security in
373 2030. *Science* **319**, 607–610 (2008).
- 374 23. Maltais-Landry, G. & Lobell, D. B. Evaluating the contribution of weather to maize
375 and wheat yield trends in 12 U.S. counties. *Agron. J.* **104**, 301–311 (2012).
- 376 24. Schlenker, W. & Roberts, M. J. Nonlinear temperature effects indicate severe
377 damages to US crop yield under climate change. *Proc. Natl. Acad. Sci. USA* **106**,
378 15594–15598 (2009).

- 379 25. Ziska, L. H. & Bunce, J. A. Predicting the impact of changing CO₂ on crop yields:
380 some thoughts on food. *New Phytol.* **175**, 607-618 (2007).
- 381 26. Ainsworth, E. A. Rice production in a changing climate: a meta-analysis of
382 responses to elevated carbon dioxide and elevated ozone concentration. *Global*
383 *Change Biol.* **14**, 1642-1650 (2008).
- 384 27. Howden, S. M. *et al.* Adapting agriculture to climate change. *Proc. Natl. Acad. Sci.*
385 *USA* **104**, 19691-19696 (2007).
- 386 28. Hall, A. J. & Richards, R. A. Prognosis for genetic improvement of yield potential
387 and water-limited yield of major grain crops. *Field Crop. Res.* **143**, 18-33 (2013).
- 388 29. Fisher, G. How do climate change and bioenergy alter the long-term outlook for
389 food, agriculture and resource availability? Food and Agriculture Organization of the
390 United Nations Economic and Social Development Department. (2009).
- 391 30. Porter, J. R. *et al.* In *Climate Change 2014: Impacts, Adaptation and Vulnerability:*
392 *Contribution of Working Group II to the Fifth Assessment Report of the*
393 *Intergovernmental Panel on Climate Change*, Field, C. B. *et al.*, Eds. (Cambridge
394 Univ. Press, Cambridge, 2014), pp. 485–533.

395 31. Hempel, S., Frieler, K., Warszawski, L., Schewe, J. & Piontek, F. A trend-
396 preserving bias correction—the ISI-MIP approach. *Earth Syst. Dyn.* **4**, 219–236
397 (2013).

398

399 **Acknowledgements**

400 We thank the Intersectoral Impact Model Intercomparison Project (ISI-MIP) and
401 the Agricultural Model Intercomparison and Improvement Project (AgMIP) for
402 providing crop model simulation results. We also thank Dr. Senthold Asseng for helpful
403 comments. This study was supported by the National Natural Science Foundation of
404 China (41561134016 and 41530528), 111 project, and National Youth Top-notch Talent
405 Support Program in China. P.C., I.J. and J.P. research was supported by the European
406 Research Council Synergy grant ERC-2013-SYG-610028, IMBALANCE-P. C.M.
407 acknowledges financial support from the MACMIT project (01LN1317A) funded
408 through the German Federal Ministry of Education and Research (BMBF).

409 **Author contributions**

410 S.L.P. designed research; C.Z. performed analysis; and all authors contributed to
411 the interpretation of the results and the writing of the paper.

412 **Author information**

413 Reprints and permissions information is available at www.nature.com/reprints.

414 The authors have no competing financial interests. Correspondence and requests for
415 materials should be addressed to S.L.P. (slpiao@pku.edu.cn)

416

417 **Figure legends**

418 **Figure 1. Future climate change (2070–2099, RCP 8.5) and its impact on global**

419 **rice yield (in comparison to 1971–2000 baseline) from an ensemble of seventeen**

420 **GGCM-CMs without CO₂ fertilization effects. a,** Growing-season temperature

421 **change. b,** Relative yield change (reproduced by ref.18). **c,** The sensitivity of rice yield

422 to climate change (). The dashed lines represent the median value of the ensemble.

423 GFDL, HadGEM2, IPSL, MIROC, and NorESM1 represent the climate models

424 GFDLESM2M, HadGEM2-ES, IPSL-CM5A-LR, MIROC-ESM-CHEM and

425 NorESM1-M,

426 respectively.

427

428 **Figure 2. Constraint on the long-term sensitivity of rice yield to temperature**

429 **change. a,** The relationship between global long-term temperature sensitivity of rice

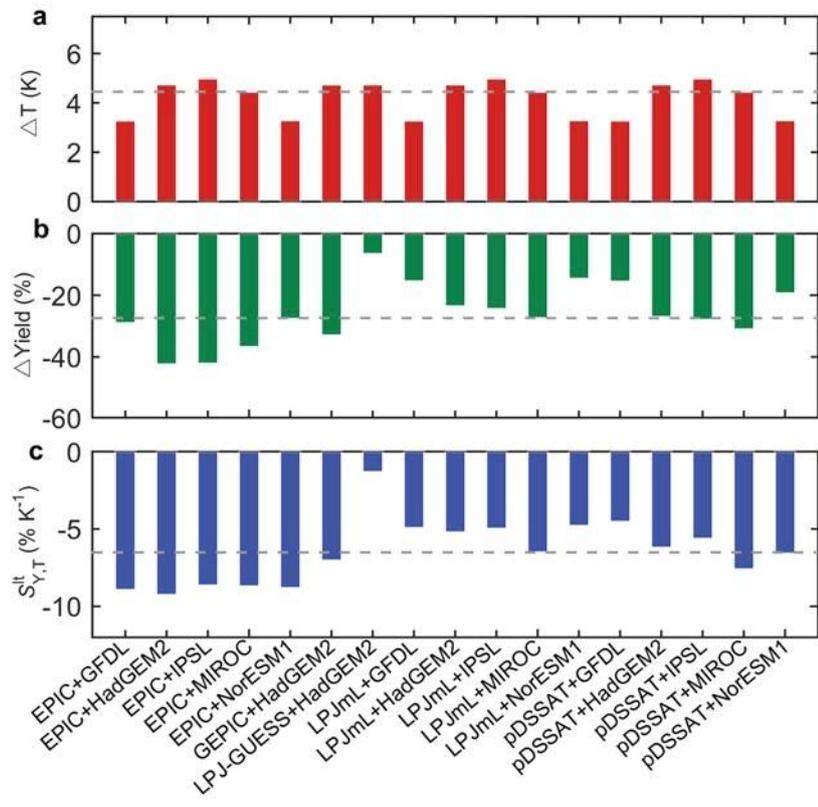
430 yield (ΔY) and site-scale present-day rice yield sensitivity to temperature across an
431 ensemble of seventeen GGCM-CMs. The red line shows the temperature sensitivity
432 estimates (ΔY , mean \pm standard deviation) from field warming experiments. **b**, Probability
433 distribution of ΔY . The black line in **b** is the probability distribution of unconstrained ΔY ,
434 assuming all the components of the ensemble can be represented by a Gaussian
435 distribution; the red dashed line is the experimental data-constrained probability
436 distribution of ΔY .

437

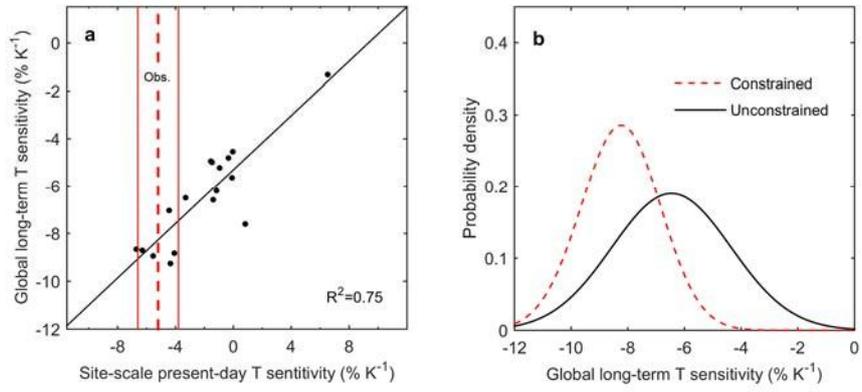
438 **Figure 3. The estimates of ΔY from four distinct approaches: global gridded crop**
439 **models (GGCMs), local crop models, statistical models and field warming**
440 **experiments. a**, Map of the study sites from local crop models, statistical models and
441 field warming experiments. The regional-scale studies are represented by the
442 corresponding label in the centre of the region (one global-scale study is not shown). **b**,
443 The estimates of all the present-day and long-term ΔY . The ΔY from GGCMs are averages
444 of all the global grid cells but not the grid cells where field warming
445 experiments are located. Error bars show the standard deviation.

446

447 **Figure 1**



448 **Figure 2**



449 **Figure 3**

450

