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► To cite this version:

Jin Fu, Yiwei Jian, Xuhui Wang, Laurent Li, Philippe Ciais, et al.. Extreme rainfall reduces one-twelfth of China's rice yield over the last two decades. *Nature Food*, 2023, 4 (5), pp.416-426. 10.1038/s43016-023-00753-6 . hal-04299080

HAL Id: hal-04299080

<https://hal.science/hal-04299080>

Submitted on 22 Nov 2023

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Extreme rainfall reduces one-twelfth of China's rice yield

Jin Fu^{1†}, Yiwei Jian^{1†}, Xuhui Wang^{1†}, Feng Zhou^{1*}, Laurent Li², Philippe Ciais^{3,4}, Jakob Zscheischler⁵, Yin Wang⁶, Yanhong Tang⁶, Christoph Müller⁷, Heidi Webber⁸, Bo Yang⁹, Yali Wu¹⁰, Qihui Wang¹, Xiaoqing Cui¹, Weichen Huang¹, Yongqiang Liu¹¹, Shilong Piao^{1,12}

¹Sino-France Institute of Earth Systems Science, Laboratory for Earth Surface Processes, College of Urban and Environmental Sciences, Peking University; Beijing, China.

²Laboratoire de Météorologie Dynamique, CNRS, Sorbonne Université; Paris, France.

³Laboratoire des Sciences du Climat et de l'Environnement, LSCE; Gif sur Yvette, France.

⁴Climate and Atmosphere Research Center (CARE-C), The Cyprus Institute; Nicosia, Cyprus.

⁵Department of Computational Hydrosystems, Helmholtz Centre for Environmental Research – UFZ; Leipzig, Germany.

⁶Institute of Ecology, Laboratory for Earth Surface Processes, College of Urban and Environmental Sciences, Peking University; Beijing, China.

⁷Potsdam Institute for Climate Impact Research (PIK), Member of the Leibniz Association, Potsdam, Germany.

⁸Leibniz Centre for Agricultural Landscape Research, Müncheberg, Germany.

⁹Key Laboratory of Nonpoint Source Pollution Control, Institute of Agricultural Resources and Regional Planning, Chinese Academy of Agricultural Sciences; Beijing, China.

¹⁰National Engineering Laboratory for Lake Pollution Control and Ecological Restoration, Chinese Research Academy of Environmental Sciences; Beijing, China.

¹¹State Key Laboratory of Plant Genomics, Institute of Genetics and Developmental Biology, Chinese Academy of Sciences; Beijing, China.

¹²Key Laboratory of Alpine Ecology, Institute of Tibetan Plateau Research, Chinese Academy of Sciences; Beijing, China

†These authors contributed equally to this work.

*Corresponding author. Email: zhouf@pku.edu.cn

1 **Extreme climate events constitute a major risk to global food production. Among**
2 **these, the extreme rainfall is often dismissed from historical analyses and future**
3 **projections, whose impacts and mechanisms remain poorly understood. Here, we**
4 **find that rice yield reductions due to extreme rainfall in China were comparable**
5 **to those induced by extreme heat over the last two decades, reaching $7.3 \pm 0.7\%$**
6 **(one standard error) according to nationwide observations and $8.1 \pm 1.1\%$**
7 **according to the crop model incorporating the mechanisms revealed from**
8 **manipulative experiments. Extreme rainfall reduces rice yield mainly by limiting**
9 **nitrogen availability for tillering that lowers per-area effective panicles and by**
10 **exerting physical disturbance on pollination that declines per-panicle filled grains.**
11 **Considering these mechanisms, we projected ~8% additional yield reduction due**
12 **to extreme rainfall under warmer climate by the end of the century. These findings**
13 **demonstrate the critical importance to account for extreme rainfall in food**
14 **security assessments, posing greater challenges to climate change adaptation.**

15 Extreme climate events have been recognized as a major risk induced by climate
16 change¹. Agricultural ecosystems are among the most vulnerable to climate extremes,
17 resulting in remarkable damage to crop production^{2,3}. For example, extreme climate
18 events have been shown to account for 18-43% of the observed anomalies in global
19 crop yields⁴. The consequences of such yield anomalies vary from fluctuations in food
20 prices, destabilized food supply, to famines⁵. As such, understanding the impacts of
21 extreme climate events on crop yield is critical for adapting food systems to future
22 climate change and thus contributing to food security for the growing global
23 populations. Recent studies have focused on elucidating impacts of drought^{6,7}, extreme
24 heat^{8,9} and cold spells¹⁰, but the impact of extreme rainfall on yields remain largely
25 uncertain^{11,12}.

26

27 Estimating the yield loss due to extreme rainfall needs to assess the magnitude of
28 extreme rainfall and timing of crop exposure, both of which are highly heterogeneous
29 over space and time. Spatially, previous studies based on yield statistics and climate
30 variables aggregated at administration zones may have smoothed out the highly
31 localized extreme rainfall events, resulting in minimal impact of extreme rainfall being
32 detected ($-0.6 \pm 1.2\%$, mean \pm standard error), which is far below the observational
33 damages from other climate extremes (e.g., $-8.1 \pm 3.1\%$ from extreme heat, $-5.2 \pm 2.8\%$
34 from drought, and $-10.2 \pm 6.5\%$ from extreme cold; [Supplementary Table 1](#)).
35 Temporarily, the exposure of crops to extreme rainfall can be dismissed if using climate
36 data with coarse temporal resolution to explore the climate-yield relationships³. The

37 lack of clear mechanistic evidence for extreme rainfall impacts^{4,11} has also rendered
38 crop modelers to dismiss their potential effects in projecting the impacts of climate
39 change¹³, despite the expected increase in occurrence of extreme rainfall¹⁴.

40

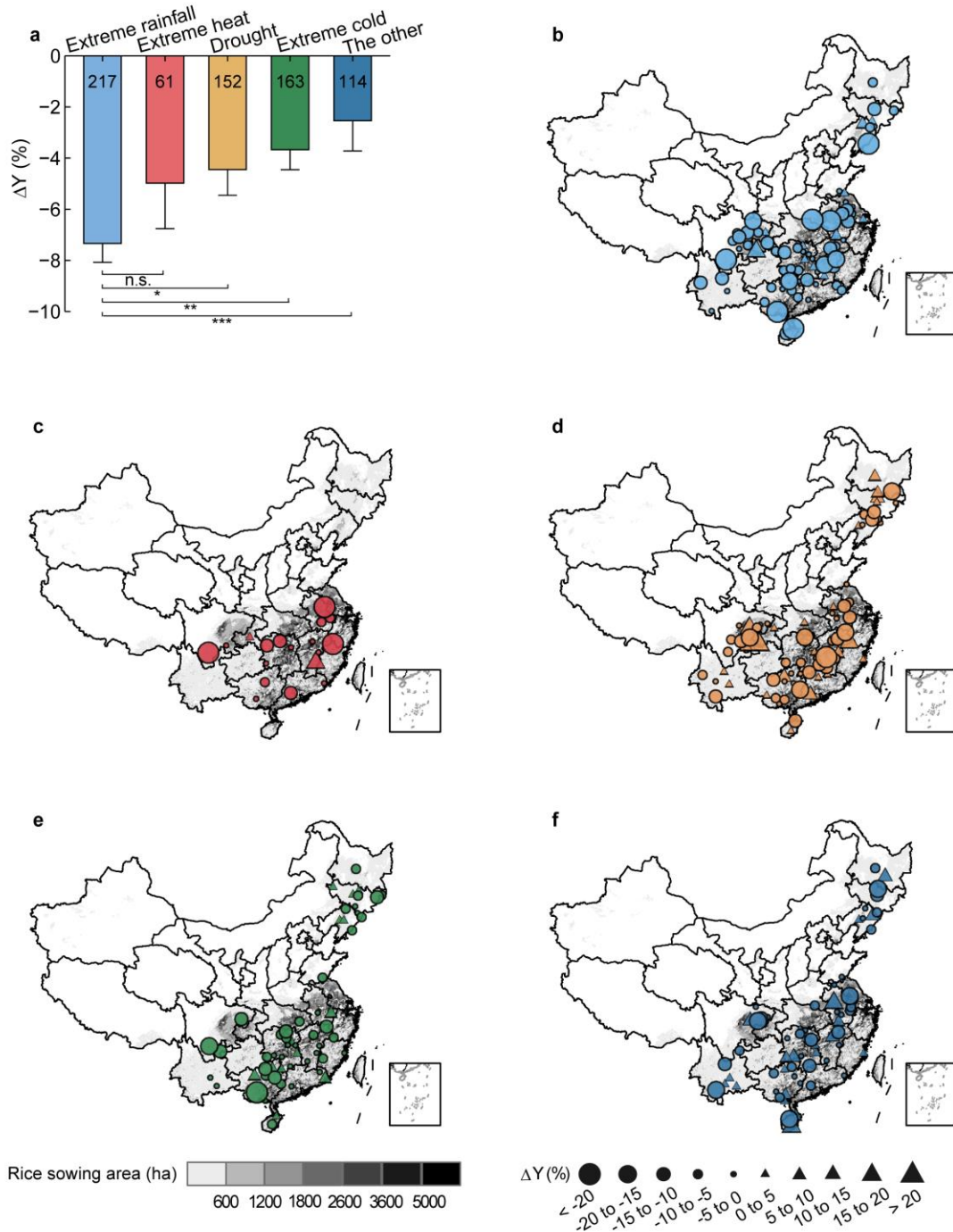
41 Rice is the primary calorie source for more than 50% of the world's population, with
42 the largest production in China¹⁵. Rice is generally considered to be strongly tolerant to
43 extreme rainfall, though this may be an artifact of relatively intense irrigation and
44 drainage management that minimizes adverse effects of rainfall anomalies^{16,17}. As a
45 result, extreme rainfall impacts on rice yield remain poorly investigated. Here, we used
46 long-term nationwide observations and multi-level rainfall manipulative experiments
47 to explore the magnitude and mechanisms of extreme rainfall impacts on rice yield in
48 China (see [Methods, Supplementary Figs 1 and 2](#)). We further improved a process-
49 based crop model by explicitly accounting for the relevant mechanisms to hindcast and
50 project the yield responses to extreme rainfall across China. This combination of field
51 observation, manipulative experiment, and model simulation enables us to address three
52 questions here: what is the magnitude and pattern of change in rice yield due to extreme
53 rainfall? what are the key mechanisms determining rice yield response to extreme
54 rainfall? how strongly do changes in extreme rainfall impact future rice yield?

55

56 **Evidence from nationwide observations**

57 We used a window searching strategy¹⁸ to isolate change in rice yield (ΔY) induced by

58 each extreme climate event for specific site and year combinations from the nationwide
59 observations (see [Methods](#), an example in [Supplementary Fig. 3](#), and the definition of
60 [events in Supplementary Table 2](#)). ΔY is defined as the relative change in rice yield
61 between the treatment and control cases (in %), after excluding the effects from the
62 other meteorological indicators and changes in rice cultivar and phenology, where in
63 the treatment rice has been exposed to a given extreme event during the rice growing
64 season, and in the control rice has not been exposed to that event and other extreme
65 events either did not occur or were the same as in the treatment. This yielded 707 ΔY
66 data at 114 sites covering most of rice production areas in China ([Supplementary Fig.](#)
67 [1b](#)). These data show that extreme rainfall induced a significant yield reduction by
68 $7.3 \pm 0.7\%$ (one standard error) in China ($n = 217$, $P < 0.001$, [Fig. 1a](#)). Such yield
69 reduction is roughly equivalent to 9 times the annual rice yield growth over the past
70 three decades ($0.8\% \text{ yr}^{-1}$, [Supplementary Fig. 4](#)). Counter-intuitively, the yield
71 reduction due to extreme rainfall was comparable to that due to extreme heat ($5.0 \pm 1.8\%$,
72 $n = 61$), and larger than the reductions related to drought ($4.4 \pm 1.0\%$, $n = 152$), extreme
73 cold ($3.7 \pm 0.8\%$, $n = 163$), and the other extreme events (e.g. hail, typhoon and tropical
74 cyclones, $2.5 \pm 1.2\%$, $n = 114$, [Fig. 1a](#)). The larger ΔY for extreme rainfall in relative to
75 other extreme events is robust when comparing different extreme events with similar
76 probability of occurrence ([Supplementary Fig. 5](#)). Spatial analyses further confirm that
77 the negative effects of extreme rainfall on rice yield are more pervasive and stronger
78 than those of other extreme events, even though record yield reductions ($\Delta Y < -20\%$)
79 can arise from any type of extreme events considered here ([Fig. 1b-f](#)).



80

81 **Fig. 1. Changes in rice yield (ΔY) induced by extreme climate events in China. a.**
 82 **The mean and standard error of ΔY from 1,000-time bootstrap estimates. b-f.** Pattern
 83 **of ΔY induced by extreme rainfall, extreme heat, drought, extreme cold, and the other**
 84 **events (typhoon and tropical cyclones), respectively. The digits noted at the base of**
 85 **each bar in panel a are the number of ΔY . The Asterisks refer to statistical significance**
 86 **of the differences in mean ΔY between extreme rainfall and other events based on the**
 87 **Wilcoxon rank sum test, with * $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$, and n.s. for not**
 88 **significant. ΔY in panels b to f is presented for each site, but averaged in case of**
 89 **multiple samples.**

90

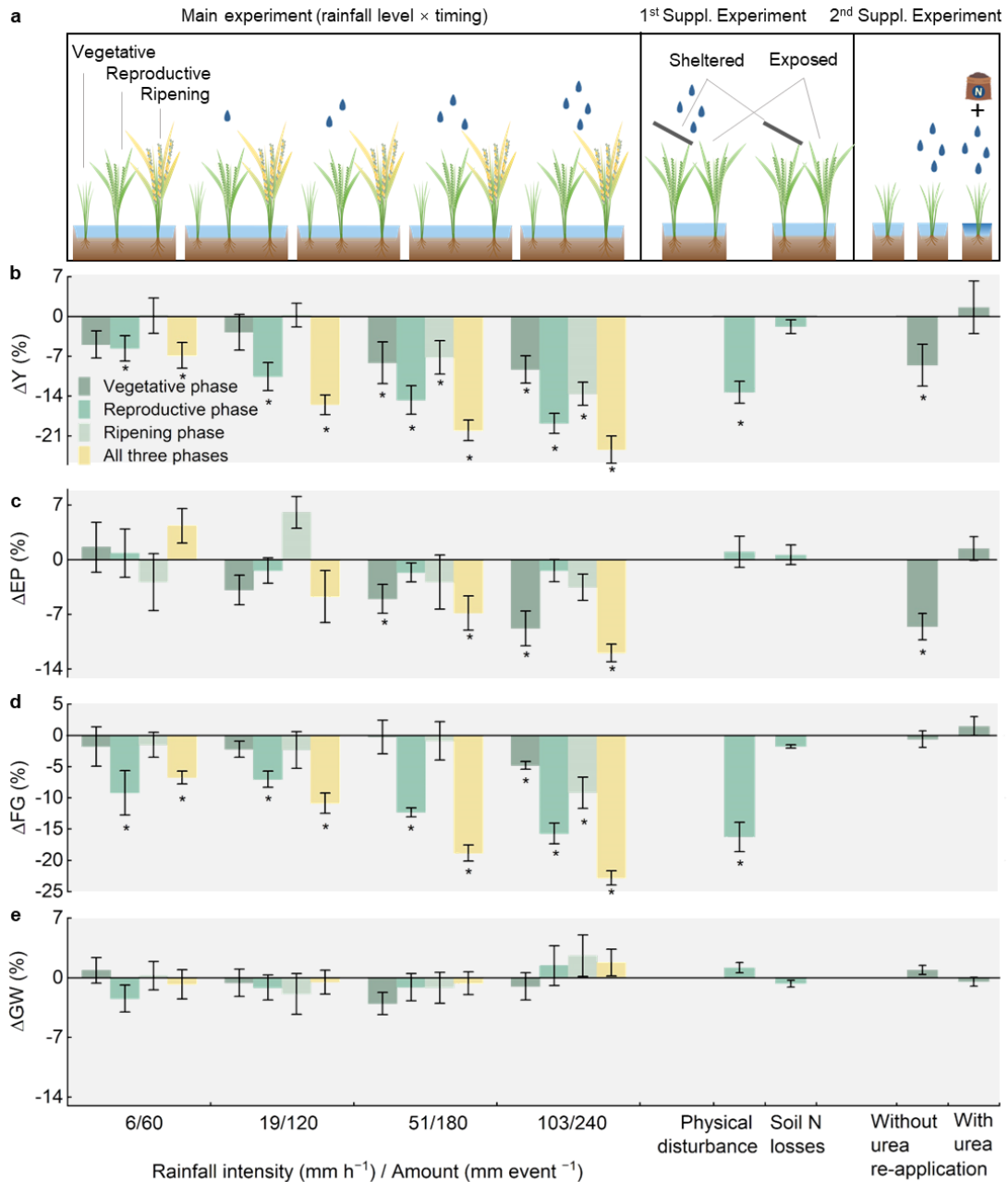
91 To identify the potential factors determining the magnitude of extreme rainfall impacts,
92 correlation analyses were performed between ΔY and extreme rainfall parameters. We
93 define extreme rainfall as the 99th percentile of hourly precipitation during rice growing
94 season for each site (see [Methods](#)). The analyses show that extreme rainfall induced ΔY
95 was negatively correlated with the intensity (cm per hour), the event amount (cm per
96 event for which the break between hourly precipitation lies below 6 hours), and the
97 event duration (hour per event) of extreme rainfall, rather than with the total intensity,
98 frequency or proportion of extreme rainfall ([Supplementary Fig. 6](#)). The combining
99 results from the Kruskal-Wallis Rank Sum Test and the Dunn's test affirmed that the
100 repeated extreme rainfall does not add to additional yield loss ([Supplementary Fig. 6g](#)).
101 These relationships are robust against variations in the definitions of extreme rainfall
102 (95th, 99th or 99.9th percentile) and of break duration (2, 6 or 12 hours) for consecutive
103 extreme rainfall events ([Supplementary Table 3](#)), confirming the key driving indicators
104 are hourly intensity and event amount rather than repeated frequencies. The sensitivities
105 of ΔY to extreme rainfall intensity and event amount were $-1.6 \pm 0.7 \% (\text{cm h}^{-1})^{-1}$ and
106 $-0.4 \pm 0.1 \% \text{cm}^{-1}$, respectively ([Supplementary Fig. 6a, d](#)). Such a sensitivity of ΔY to
107 rainfall intensity is roughly in line with previous field observations ($-1.0 \pm 0.2 \% (\text{cm}$
108 $\text{h}^{-1})^{-1}$, $n = 11$), but larger than the results from previous statistical analysis aggregated
109 at administrative scales ($-0.03 \pm 0.05 \% (\text{cm h}^{-1})^{-1}$, $n = 33$; [Supplementary Table 1](#)).

110

111 **Experimental tests of the extreme rainfall-rice yield relationship**

112 To isolate the mechanisms leading to extreme rainfall impacts on ΔY , we established a

113 series of rainfall manipulative experiments in 2018 and 2019 (see [Methods and Fig. 2a](#)
114 [for detailed setup](#)). In the experiments, we established four rainfall levels to broadly
115 represent extreme rainfall events across China's rice fields. To test if the impacts differ
116 by growth phases, rainfall manipulation was conducted for each or their combination
117 of the three phases (i.e., vegetative phase when tillers are formed, reproductive phase
118 when spikelets reach anthesis, and ripening phase when grains are filled). We quantified
119 ΔY between treatment and control plots for which two replicates were considered. In
120 agreement with the nationwide observations, ΔY was $-1.1 \pm 0.3\%$ and $-0.6 \pm 0.1\%$ in
121 response to 1-centimeter increase in extreme rainfall intensity and event amount,
122 respectively. These effect sizes were also statistically the same between the two
123 experimental years ([Supplementary Fig. 7a, b](#)). Analyses of changes in yield
124 components indicated that ΔY were mostly caused by declines in effective panicles per
125 unit land area (EP) and filled grains per panicle (FG), accounting for 22% to 25% and
126 71% to 75% of ΔY , respectively, whereas decreased grain weight (GW) only
127 contributed to approximately 1.4% to 6.0% ([Fig. 2 and Supplementary Fig. 7c](#)).
128 Extreme rainfall impacts on yield components depend on growth phase. Extreme
129 rainfall in the vegetative phase mainly reduced EP, while in the reproductive phase, it
130 mainly reduced FG. ([Fig. 2](#)).



131

132 **Fig. 2. Effects of simulated rainfall on rice yield and yield components.** **a.**
 133 Experimental setup. **b** to **e.** Relative changes in rice yield (ΔY), effective panicles per
 134 unit land area (ΔEP), filled grains per panicle (ΔFG), and grain weight (ΔGW),
 135 respectively. For the 2nd supplementary experiment, the urea re-application rate (i.e.,
 136 28.8 kg N ha⁻¹) is equal to the average N losses observed from the treatment plots using
 137 the same rainfall amount during vegetative phase in main experiments. Asterisk
 138 indicates for the significant difference with zero, with $P < 0.05$.

139

140 We hypothesized that the growth phase-dependent effects of extreme rainfall result
 141 from different mechanisms in reducing rice yield, that is, high extreme rainfall intensity

142 reduces FG through physical disturbance (in terms of kinetic energy) on pollination^{19,20},
143 and high extreme rainfall event amount stresses tillering through inducing soil N
144 losses^{21,22}. To test these hypotheses, we conducted two supplementary experiments
145 using the maximum rainfall level (103 mm per hour for intensity or 240 mm per event
146 for event amount) in 2021 (see [Methods](#)).

147

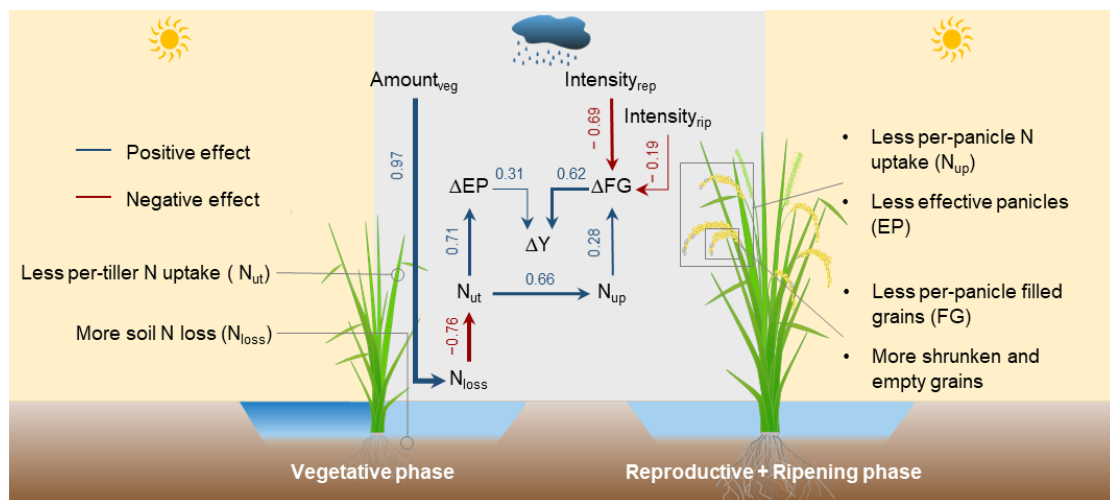
148 In the first supplementary experiment, we sheltered half of each rice plot during the
149 reproductive phase so that the sheltered halves of treatment were affected by extreme
150 rainfall only through its effects on soil N losses, but not direct physical disturbance ([Fig.](#)
151 [2a and Supplementary Fig. 8](#)). We found FG in the sheltered halves of treatment show
152 little difference (< 2.0%) with the control, while FG in the exposed halves of treatment
153 decreased by $18.0 \pm 2.6\%$ ([Fig. 2](#)). The empty or shrunken grains were found mostly in
154 the upper part of the panicles of the exposed halves of treatment ([Supplementary Fig.](#)
155 [9](#)), further supporting that FG were reduced by the physical disturbance that prevents
156 successful pollination, a critical process of yield formation.

157

158 The second supplementary experiment isolates the effects of soil N losses induced by
159 extreme rainfall event amount during the vegetative phase ([Supplementary Fig. 8a](#)). We
160 supplied additional urea to half of the treatments, so that if there was a soil N loss
161 induced by the extreme rainfall, it would be compensated. We found that urea re-
162 application could help maintain N uptake per tiller, and thus successfully stabilized EP

163 and rice yield (Fig. 2). Treatments that did not compensate for N losses caused
 164 proportionally similar declines in N uptake per tiller and thereby EP ($R^2 = 0.70$ and
 165 0.57 , respectively, $P < 0.001$, Supplementary Fig. 10). These findings confirm that the
 166 reduced EP was primarily attributable to extreme rainfall event amount that limits soil
 167 N availability and crop N uptake causing lower yields.

168



169

170 **Fig. 3. Schematic diagram of extreme rainfall impacts on rice yield.** Single-headed
 171 arrows indicate the direction of causation identified by the structural equation
 172 modelling. Blue (red) arrows indicate significant positive (negative) effects ($P < 0.05$).
 173 Arrow width is proportional to the strength of the relationship, which is characterized
 174 by standardized path coefficients showing next to arrows. Amount_{veg}, extreme rainfall
 175 event amount in vegetative phase; Intensity_{rep} and Intensity_{rip}, extreme rainfall intensity
 176 in reproductive and ripening phases, respectively; ΔY , relative changes in rice yield.

177

178 Ultimately, we summarized and tested our findings from the experiments with structural
 179 equation modelling (SEM) to illustrate the mechanisms by which extreme rainfall
 180 reduces rice yield (Fig. 3). The SEM including the direct pathways of rainfall-induced
 181 physical disturbance and soil N losses shows the best performance (Supplementary Fig.
 182 11a), explaining 56% of the overall variance in rice yield reductions. This suggests that
 183 both pathways are primary mechanisms explaining ΔY , whereas other potential

184 mechanisms (e.g., changes in photosynthesis, leaf area index, phosphorous loss,
185 phosphorous and potassium absorptions) do not show significant effects
186 ([Supplementary Fig. 11b-f](#)). In addition to these two pathways, the best-fit SEM also
187 identified an indirect pathway, i.e., rainfall-induced N losses during the vegetative
188 phase, which may also limit per-panicle N uptake during the reproductive phase thereby
189 decreasing FG ([Fig. 3 and Supplementary Fig. 11a](#)).

190

191 **Crop model improvements for assessing ΔY**

192 Correctly representing the mechanisms through which extreme rainfall reduces rice
193 yield is critical for diagnosing and projecting spatiotemporal variations in rice yield.
194 We introduced the first physical disturbance module of extreme rainfall on rice yield in
195 ORganizing Carbon and Hydrology in Dynamic EcosystEms for crops (ORCHIDEE-
196 crop)²³, which is a process-based crop model including the representation of single,
197 early and late rice types, paddy rice irrigation, and a detailed soil hydrology model²⁴.
198 The direct and indirect pathways of extreme rainfall through soil N losses was also
199 introduced into the model (see [Methods and Supplementary Table 4](#)). The improved
200 model can robustly capture the observed rice yield variability due to year-to-year
201 climate variations and extreme rainfall treatments (the coefficient of determination of
202 0.88 in 2018 and 0.78 in 2019, mean root square error of 0.69 in 2018 and 1.19 in 2019,
203 [Supplementary Fig. 12](#)). The model was further validated by field observations of rice
204 yield in 2021 between control and treatment ([Supplementary Fig. 12](#)).

205

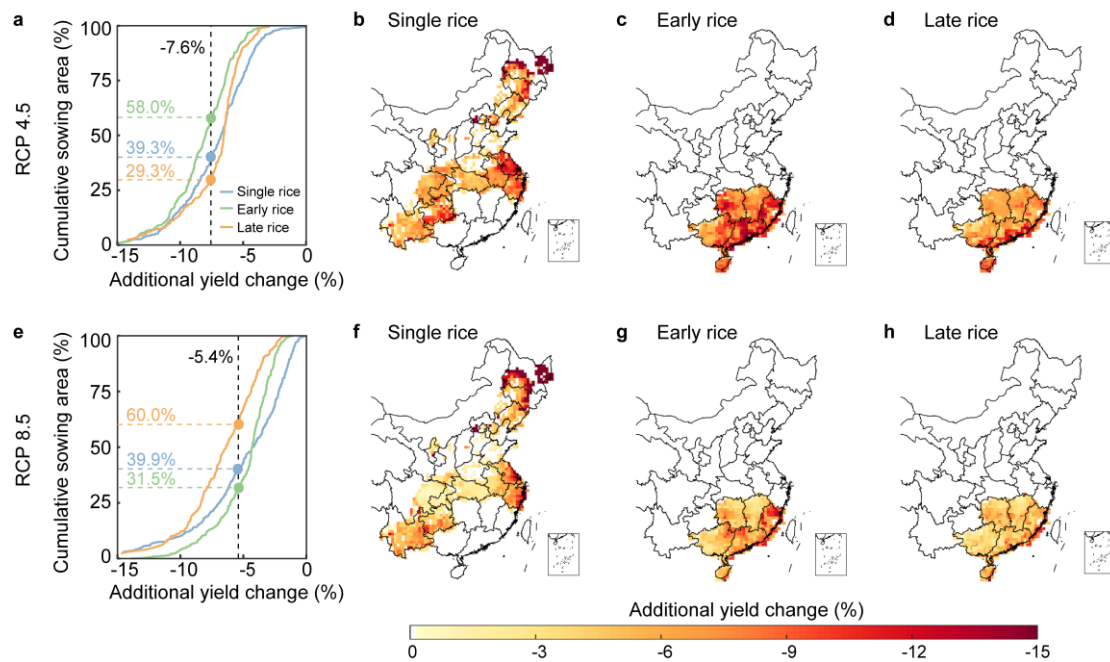
206 We then used the high-resolution global precipitation measurement (GPM) datasets²⁵
207 to drive the improved model over China in 2001-2016 (see [Methods](#)). On average, the
208 improved model hindcasts lower rice yields due to the extreme rainfall by $8.1 \pm 1.1\%$
209 (one standard error for interannual variability) for all rice types, $8.3 \pm 1.0\%$ for single
210 rice, $8.6 \pm 1.0\%$ for early rice, and $7.6 \pm 1.3\%$ for late rice ([Supplementary Fig. 13a-c](#)).
211 Higher ΔY were simulated eastern China and southern coastal regions which
212 experienced higher rainfall intensities ([Supplementary Fig. 13a-c](#)). Factorial model
213 simulations show that physical disturbance induced by extreme rainfall was the most
214 important determinant across 47-95% of rice sowing areas ([Supplementary Fig. 13d-f](#)),
215 leading to yield losses of 3.9% for single rice, 5.1% for early rice, and 4.1% for late
216 rice. Extreme rainfall-induced N losses dominated the ΔY mainly in Anhui and Jiangsu
217 provinces where both N application rates²⁶ and extreme rainfall event amount were
218 relatively high²⁷ ([Supplementary Fig. 13h-j](#)).

219

220 **Projected impacts of future change in extreme rainfall**

221 Since extreme rainfall was found to have significant impacts on historical rice yields, a
222 process which was neglected in previous projections under climate change^{28,29}, we
223 made a first attempt to project the risk of future rice yield to changing extreme rainfall
224 dynamics. We used the high-resolution climate projection by the IPSL model zoomed
225 over China³⁰, which performed well in reproducing the spectral properties of rainfall

226 including extreme events³¹, to drive the improved model under two climate scenarios
227 (representative concentration pathways [RCP] 4.5 and 8.5; see [Methods](#)). Considering
228 extreme rainfall impacts led to greater projected yield reductions by the end of this
229 century (2085-2100, [Fig. 4](#)). On average, extreme rainfall induces an additional yield
230 reduction of 7.6% in China on the top of other climate-change induced impacts under
231 RCP 4.5. We then ranked the additional yield reductions in grid cells from the largest
232 to smallest and calculated the cumulative sowing area affected by a given additional
233 yield change, and found that the sowing areas with additional yield reduction of >7.6%
234 accounted for 58% for early rice, 39% for single rice, and 29% for late rice ([Fig. 4a](#)).
235 Rice is projected to suffer from extreme rainfall events the most over northeast China
236 and southeast coastal regions ([Fig. 4b-d](#)). However, additional yield reductions were
237 projected to be weaker under RCP 8.5 relative to RCP 4.5 ([Fig. 4e-h](#)), with the national
238 mean reduction due to extreme rainfall of 5.4%, mainly because of larger rice yield
239 reduction induced by stronger warming and carbon dioxide concentrations under RCP
240 8.5 together with no differences in projected extreme rainfall between the two scenarios
241 ([Supplementary Fig. 14](#)). These new projections highlight the increasing risk of rice
242 yield reductions induced by extreme rainfall and an urgent need to consider this risk in
243 planning climate change adaptations.



244

245 **Fig. 4. Future projections of additional yield change induced by extreme rainfall.**

246 **a** and **e**. cumulative proportions of sowing area affected by a given additional yield

247 change under RCP 4.5 and RCP 8.5, respectively; Black dashed lines represent the

248 national means (-7.6% and -5.4%), and the numbers represent the cumulative

249 proportions of sowing area affected by exceeding the national means. **b** to **d**. Patterns

250 of ΔY under RCP 4.5. **f** to **h**. Same as panels **b** to **d** but under RCP 8.5.

251

252 Discussion

253 While both nationwide observations and model simulations indicated approximately 8%

254 of rice yield lost in China due to extreme rainfall, we note that our analyses are subject

255 to several sources of uncertainties. On the observation side, due to rigorous screening

256 criteria to isolate extreme rainfall impacts from other extreme events, rice yield

257 assessment has been eliminated over the Southeast Coast where extreme rainfall is

258 strong ([Supplementary Figs 1b and 15](#)), likely underestimating the extent of extreme

259 rainfall induced ΔY . On the modelling side, extreme rainfall intensity and event amount

260 used for driving the historical simulations across China were from the half-hourly and

261 0.1-degree GPM dataset, which is well represented for but still did not fully capture the

262 observed heaviest rainfall extremes ([Supplementary Fig. 16](#)). Thus, our estimates of
263 extreme rainfall impact on rice yield should be viewed as a conservative assessment.
264 Another source of uncertainty is related to the setup of our manipulative experiments.
265 The experiments were conducted on cloudy days to approximate natural rainfall
266 conditions, but muted the effects of accompanying processes such as reduced air
267 temperature³² and enhanced waterlogging³³. These accompanying processes may cause
268 rice diseases and lodging that can further compound rice yield responses^{12,34}. Moreover,
269 our experiment focused on uncovering mechanisms of extreme rainfall impacts under
270 regular management, without climatic adaptations, which introduces additional
271 uncertainties in future projection.

272

273 Although we focused on rice yields in China that is the largest rice producer globally,
274 attention to other rice producing regions may yield critical insights into the
275 biogeography and generalizability of our findings. Compared to China, rice fields in
276 South and Southeast Asia have smaller N application rates and larger fractions of
277 rainfed rice ([Supplementary Fig. 17](#)). Extreme rainfall in these regions may lead to a
278 lower risk of soil N losses and thus lower impacts on tillering. However, these regions
279 were more exposed to extreme rainfall given much higher extreme rainfall intensity
280 ([Supplementary Fig. 15b](#)), and thus subject to higher risk of physical disturbance. Since
281 across approximately 80% of China's rice fields, extreme rainfall impacts results from
282 direct physical disturbance on pollination, rice yield reductions in South and Southeast
283 Asia should also be significant. Previous projection of rice yield response to climate

284 change without considering the extreme rainfall impacts (e.g., Webber et al.¹³,
285 Rosenzweig et al.²⁸, Jägermeyr et al.²⁹, Iizumi et al.³⁵) have likely been overly
286 optimistic in this regard.

287

288 The impacts of extreme rainfall on other staple crops such as wheat and maize remain
289 to be explored. Although the magnitude and mechanistic representation of rice yield
290 response to extreme rainfall may not be directly applicable to other crops, our research
291 paradigm that combines field observations, manipulative experiments, and processed-
292 based modelling is well transferable. Unlike rice, sizable fraction of upland crops were
293 rainfed or under different irrigation-drainage systems³⁶. The sensitivity of tillering and
294 pollination processes in response to extreme rainfall may also be different from what
295 we observed here. Therefore, a major research challenge remains to assess the global
296 extreme rainfall impacts for all cereal crops.

297

298 **Methods**

299 **Analysis of nationwide observational data**

300 *Yield change induced by extreme climate events.* We collected field observations of rice
301 yield and extreme climate events from the national agrometeorological observation
302 network that is run by the China Meteorological Administration (CMA). This network
303 covers most rice production areas, including single rice in northeast and central China
304 and early and late rice in south China ([Supplementary Fig. 1a](#)). It provides rice yield of

305 2,304 site-year records from 166 sites, and extreme climate events of 8,595 records
306 from 356 sites occurred in the rice growing seasons over the period 1999-2012. Rice
307 yield is defined as actual production divided by the hectare of harvested area. Extreme
308 climate events are recorded on given days for each site and are sorted into five broad
309 categories, i.e., extreme heat, extreme cold, extreme rainfall, drought, and the other
310 events (see definitions in [Supplementary Table 2](#)).

311

312 First, the field observations are reproduced by summing the detrended yield and the
313 multi-year average (Y_{de}) for each site and rice type, to avoid the impacts of changing
314 rice cultivar, phenology and technology. Second, to exclude the effects of the other
315 meteorological indicators on yield, a multiple linear regression analysis is applied for
316 Y_{de} against mean temperature, total precipitation and total sunshine hours during rice
317 growing season for each site and rice type. Regression coefficients are determined as
318 the median of 1,000-time bootstrap estimates, and used for predicting yield ($Yfit_{de}$).
319 Third, a window searching strategy¹⁸ is applied to find all available control-treatment
320 pairs (YC and YT) to quantify rice yield change (ΔY) induced separately by different
321 extreme events for a given site and year ([Supplementary Fig. 3](#)):

$$322 \quad \Delta Y = \frac{(YT_{de} - YTfit_{de}) - (YC_{de} - YCfit_{de})}{YC_{de}} \times 100\% \quad (1)$$

323 This strategy expands on previous studies^{3,11,12,37-42} in at least three aspects: (i) It
324 ensures both control and treatment sharing approximately the same management
325 practices (e.g., fertilization, irrigation, and drainage) and geographical conditions (e.g.,
326 soil properties and topography), while almost avoiding technology- or cultivar-driven

327 change in rice yield; (ii) it isolates the impact of a given extreme event on rice yield
328 while largely reducing the noise due to the other events, and (iii) it provides an
329 observational evidence for climate extreme impacts on rice yield at the site scale, rather
330 than expected signal from statistical inferences at administrative scales. Finally, a
331 dataset of 707 control-treatment pairs from 114 sites were identified, i.e., 217 pairs for
332 extreme rainfall at 82 sites, 152 pairs for drought at 73 sites, 61 pairs for extreme heat
333 at 18 sites, 163 pairs for extreme cold at 61 sites, and 114 pairs for the other events at
334 68 sites ([Supplementary Fig. 1b and Data 1](#)).

335

336 The Wilcoxon rank sum test was applied to assess the significance of ΔY . The choice is
337 motivated by the fact that ΔY is not normally distributed (Kolmogorov-Smirnov test, P
338 < 0.05). The Wilcoxon rank sum test was also applied to quantify the difference between
339 extreme rainfall and other extreme events. To solve the inconsistency of sample size
340 among the extreme events, we applied the bootstrap resampling to estimate the means
341 and standard error of ΔY by randomly sampling an equal size from the initial dataset
342 for 1000 times. The results show that the differences in ΔY are robust, because ΔY are
343 dominated primarily by climate extremes with moderate effects on rice yields, rather
344 than a few outliers ([Supplementary Fig. 18](#)), and are not strongly influenced by sample
345 size ([Supplementary Fig. 19](#)). In addition, we calculated the percentiles of the extreme
346 events occurred in the period 1999-2012, and found that most of them exceed 95th
347 percentile ([Supplementary Fig. 5a-d](#)). However, these percentiles are not completely
348 consistent among the events. To test the robustness of the differences in ΔY , we

349 compared the effects of different extreme events with similar percentiles, that is, 95th to
350 99th (or 99th to 99.8th) percentiles for extreme heat and rainfall and 1st to 5th (or 0.2nd to
351 1st) percentiles for extreme cold and drought ([Supplementary Fig. 5e-f](#)).

352

353 *Sensitivity of ΔY to extreme rainfall.* We defined extreme rainfall if hourly precipitation
354 exceeds the threshold that is the 99th percentile of growing-season hourly precipitation
355 over the reference period 1981–2012 for each site. The data for hourly precipitation
356 were acquired from the CMA. To understand the main influencing factors, seven extreme
357 rainfall parameters, reflecting characteristics of intensity, event amount and repeated
358 extreme rainfalls, were then quantified during rice growing season for each treatment
359 ([Supplementary Data 1](#)), including intensity as the maximum hourly precipitation when
360 exceeding the threshold (RX1h, cm h⁻¹), total intensity as the sum of hourly
361 precipitation when exceeding the threshold (RX1hTOT, cm h⁻¹), frequency as hours or
362 the fraction of the hours when hourly precipitation exceeds the threshold to the length
363 of rice growing season in hours (R99f, hours, and R99p, %) , proportion as the sum of
364 hourly precipitation that exceeds the threshold divided by the growing-season total
365 precipitation (R99pPROP, %), event amount as the precipitation amount averaged for
366 extreme rainfall events that involve at least one extreme rainfall and for which the break
367 duration between hourly precipitation does not exceed 6 hours⁴³ (Rg1event, cm per
368 event), and event duration as the total hours of extreme rainfall events during rice
369 growing season divided by event numbers (ERED, hour per event).

370

371 We then conducted correlation analyses of the extreme rainfall induced ΔY against
372 seven parameters for identifying the potential factors. The correlation emphasizes the
373 changes in rice yields caused by the maximum precipitation intensity and event amount,
374 rather than repeated extreme rainfall events nor proportion to total precipitation amount,
375 though it may be also affected by large values of parameters over a few sites. To tackle
376 this uncertainty, we applied the bootstrap resampling to estimate the sensitivities and
377 standard error of ΔY in response to extreme rainfall by randomly sampling 90% of the
378 samples from the initial dataset for 1000 times. Besides, Kruskal-Wallis Rank Sum Test
379 and Dunn's test are applied to confirm the insignificance of extreme rainfall frequencies
380 (1, 2, 3 and ≥ 4 times) on ΔY . We also tested if ΔY response to extreme rainfall is
381 dependent on the definitions of extreme rainfall. The sensitivity analyses were
382 conducted based on the different thresholds (95th, 99th or 99.9th percentile) to define
383 extreme rainfall and based on the break duration ($\leq 2, 6, \text{ or } 12$ hours) to define extreme
384 rainfall event ([Supplementary Table 3](#)).

385

386 **Rainfall manipulative experiments**

387 *Plants and cultivation condition.* The experimental site is at the Jingzhou
388 Agrometeorological Experimental Station in Hubei province, China (30°21'N,
389 112°09'E; [Supplementary Fig. 2a](#)). It is characterized as subtropical humid monsoon
390 climate, with a mean air temperature of 16 °C and a mean precipitation of 1,095 mm
391 yr⁻¹. Soil is classified as Hydragric Anthrosol ([Supplementary Table 5](#)). Rice seedling
392 nurseries were managed under the water regime of continuous flooding. Seedlings of

393 rice (*Oryza sativa* L.) were transplanted at 30-day seedling ages with a hill spacing of
394 0.33×0.33 m (9 hills m^{-2}), and harvested after 103 days. Fertilizers of 172 kg ha^{-1} N
395 in the form of N-NH₄, 61 kg ha^{-1} P in the form of P₂O₅ and 49 kg ha^{-1} K in the form of
396 K₂O were applied over three events, that was one event with 72 kg ha^{-1} N, 53 kg ha^{-1} P
397 and 42 kg ha^{-1} K applied 1 day before rice transplanting, one with 78.7 kg ha^{-1} N
398 applied two weeks after transplantation, and one with 20.9 kg ha^{-1} N, 8 kg ha^{-1} P and
399 7 kg ha^{-1} K applied during the jointing stage. Further details on cultivation condition
400 can be found in [Supplementary Fig. 2b](#).

401

402 *Main experiment.* The rainfall manipulative experiment was conducted from 2018 to
403 2019, spanning two rice growing seasons. The experiment consisted of ambient control
404 and factorial treatments with two replicates, and was designed for extreme rainfall
405 level-timing combinations ([Supplementary Fig. 2c](#)), with the results in [Supplementary](#)
406 [Data 1](#). The treatments comprised four rainfall levels in each or all of three growth
407 phases (i.e., vegetative, reproductive, or ripening phases). There was a total of 34 plots
408 for main experiments, each of which had an area of 6 m^2 ($2 \text{ m} \times 3 \text{ m}$) and was
409 completely isolated by plastic-covering levees and impervious plates at a 0.5-meter
410 distance in between. Throughout the experiment, all plots were subjected to the same
411 agricultural management practices. To avoid the border effects, we use independent-
412 samples t-test to compare the yield of ambient control with that of three plots nearby,
413 with each plot owing 150 m^2 ($25 \text{ m} \times 6 \text{ m}$) with the same agricultural management
414 practices, and found no significant differences during three rice growing seasons

415 ($P > 0.05$, [Supplementary Fig. 20a](#)).

416

417 We manipulated rainfall levels by running the artificial rainfall manipulation system
418 (NLJY-10, Nanlin Electronics, China) for one hour on two replicates for each treatment,
419 with the rainfall amount of 60, 120, 180, and 240 mm. However, the intensities of
420 manipulative rainfall were far less than natural one because of a lower falling velocity
421 of raindrops. We thus measured the kinetic energy of manipulative rainfalls using the
422 laser precipitation disdrometer (OTT Parsivel², Hach, USA), which is equivalent to the
423 natural rainfall intensities of 6, 19, 51, and 103 mm per hour. These rainfall levels
424 represent most of the broad range of growing-season rainfall extremes (exceeding the
425 99th percentile) across China's rice fields (i.e., 8 to 143 mm per hour and 12 to 526 mm
426 per event observed in the period 1999-2012). To approximate the natural rainfall
427 condition, rainfall manipulation was conducted in cloudy daytime for vegetative and
428 ripening phases, but for reproductive phase specifically at 8:00-13:00 when spikelets
429 reach anthesis in experimental site. To minimize the impact of waterlogging, ponded
430 water was discharged within 12 hours after rainfall manipulation if the depth exceeds
431 100 mm. No plants were washed away or fell due to rainfall manipulation.

432

433 For each plot, we measured leaf area index, total tiller number, dry weights of leave,
434 stem, and panicle, which were determined from three hills with an average number of
435 tillers ([Supplementary Data 1](#)). All leaves, stems, and panicles were oven-dried
436 (DHG500, SUPO Co.) at 75°C for several days. We measured N, P, and K contents in

437 leave, stem and panicle using a continuous flow analyzer (Elementar, Germany), and
438 net photosynthesis of three flag leaves at two photosynthetic photon flux densities of
439 1500 and 600 $\mu\text{mol m}^{-2} \text{s}^{-1}$ using Li6400 (Li-Cor Inc., USA). These measurements were
440 conducted at seedling, maturity, and during three growth phases. Net photosynthesis
441 was measured before and after each rainfall manipulation. In addition, for each
442 treatment, we observed N and P losses via runoff and leaching during the period from
443 the beginning of rainfall manipulation to the time when ponded water level decreased
444 down as that before manipulation.

445

446 At maturity, three hills with an average number of panicles were collected from each
447 plot to determine the yield estimated as the product of effective panicles per unit land
448 area (EP), filled grains per panicle (FG), and grain weight (GW) ([Supplementary Data](#)
449 [1](#)). The filled grains were oven-dried at 75 °C for at least 72 h, but their weights were
450 adjusted to a fresh weight with a moisture content of 0.15 g H₂O g⁻¹, ref⁴⁴. To determine
451 actual yields, the filled grains from the other rice plant hills for all plots were machine-
452 threshed (OUGEDA Co., China) and sun-dried to reach a moisture content of 0.15 g
453 H₂O g⁻¹. The yields for all plots were highly consistent with actual ones
454 ([Supplementary Fig. 20](#)).

455

456 We calculated absolute differences in rice yield and in yield components between the
457 controls and treatments, and then converted the absolute differences to relative changes
458 (ΔY , ΔEP , ΔFG , and ΔGW in %) to simplify comparisons among treatments and with

459 the other experimental results. Note that the compensation relationship between ΔEP
460 and ΔFG if rice planting distance below 15 cm (ref⁴⁵) can be avoided in our
461 experimental plots as the distance is 30 cm. ΔY is equal to the sum of ΔEP , ΔFG , and
462 ΔGW , that is $\Delta Y = \Delta EP + \Delta FG + \Delta GW$ according to the Kaya identity principle⁴⁶. The
463 attribution results help identify the key yield components that were most affected by
464 extreme rainfall. We further identified in which growth phase extreme rainfall regulates
465 the changes in key yield components.

466

467 *1st supplementary experiment.* To isolate the mechanism driving the causal relationship
468 between extreme rainfall and ΔFG , we ran the first supplementary experiment during
469 the reproductive phase in July 2021. In the experiment, extreme rainfall intensity is 103
470 mm per hour (Supplementary Fig. 8 and Data 1). For each treatment, transparent
471 impervious film was placed above half of the plot, such that half of the plants were fully
472 exposed to artificial rainfall and the other part was sheltered but experienced the same
473 increases in ponded water levels and nutrient losses as the exposed part. To avoid an
474 unintentional influence of film on rice growth, the film was also placed above a half
475 control plots and all films were removed when the experiment ended.

476

477 FG and actual yield in exposed and sheltered parts for each plot were observed. Based
478 on the observations, we attributed the effect of extreme rainfall on ΔFG into physical
479 disturbance and soil N loss as below:

480
$$\text{Total: } \Delta Y = Y_{ROC} - Y_{COC}, \Delta FG = FG_{ROC} - FG_{COC}, \quad (2a)$$

481 Soil N loss (*o*): $\Delta Y_o = Y_{RC} - Y_{CC}, \Delta FG_o = FG_{ROC} - FG_{COC},$ (2b)

482 Physical disturbance (*p*): $\Delta Y_p = \Delta Y - \Delta Y_o, \Delta FG_p = \Delta FG - \Delta FG_o,$ (2c)

483 where *ROC* and *COC* refer to the exposed parts for treatment and control, respectively.
484 *RC* and *CC* refer to the sheltered parts for treatment and control, respectively. In
485 addition, we measured the number of empty and shrunken grains at maturity as well as
486 their distribution along panicle. Such observations further elucidate how extreme
487 rainfall influences rice pollination during reproductive phase.

488
489 ^{2nd} *supplementary experiment*. To confirm the causal effect of extreme rainfall on ΔEP ,
490 we ran the second supplementary experiment during vegetative phase in June 2021. The
491 rainfall amount is 240 mm. The experiment consisted of ambient control and two
492 treatments ([Supplementary Fig. 8a](#) and [Data 1](#)). For treatments, rice plants were fully
493 exposed to artificial rainfall on 6 plots, half of which were re-applied by 28.8 kg N ha⁻¹
494 (37% of tillering fertilizer application) in the form of urea after rainfall manipulation.
495 The re-application rate was determined as the average of observed N losses from the
496 treatment plots using the same rainfall amount during vegetative phase in 2018 and
497 2019.

498
499 For each plot, we observed EP and the actual yield at maturity as well as N uptake per
500 tiller from transplantation to panicle initiation. Based on the observations, we tested the
501 differences in these three indicators between treatments and controls using the
502 Wilcoxon rank sum test. If no significant differences between N re-applied treatment

503 and control but significant differences between normal treatment and control were
504 found, the decrease in EP were attributed to N losses induced by extreme rainfall during
505 the vegetative phase.

506

507 *Path analysis.* Structural equation modelling (SEM) implemented in the R package
508 ‘lavaan 0.6-7’⁴⁷ allows us to test different hypotheses governing the pathways by which
509 extreme rainfall affects rice yield. On the basis of potential causal relationships revealed
510 by our experiments and previous literatures⁴⁸⁻⁵⁰, a series of SEMs were formulated
511 (Supplementary Fig. 11). The insignificant paths ($P > 0.05$) were eliminated gradually
512 until all links significantly contributed to the final model. To compare model
513 performance, we conducted a chi-squared difference test and calculated model fit
514 statistics (root mean square error of approximation [RMSEA], comparative fit index
515 [CFI], goodness-of-fit index [GFI] and adjusted R squared [R_{adj}^2]). Standardized path
516 coefficients were computed according to ref.⁵¹, which can be interpreted as the change
517 in the dependent variable when the independent variable changes by one standard
518 deviation.

519

520 **Process-based modelling for regional assessments**

521 We improved the process-based crop model ORCHIDEE-crop^{23,24,52} to account for the
522 impacts of extreme rainfall according to the mechanisms revealed by our rainfall
523 manipulative experiments. We first tested its performance at the experiment sites driven
524 by climate data observed in 2018 and 2019, and further validated by additional

525 observations in the supplement experiment year (2021), and then used the improved
526 model to hindcast and project the impacts of extreme rainfall on rice yield across China
527 during 2001-2016 and 2085-2100 under two Representative Concentration Pathways
528 (RCP 4.5 and 8.5).

529

530 *Model improvement.* ORCHIDEE-crop simulates crop phenology, leaf area dynamics,
531 growth of reproductive organs, carbon allocation and managements, as well as carbon,
532 water and energy fluxes of agroecosystems. This model has been applied globally and
533 regionally, and found to robustly reproduce yield variability⁵³. ORCHIDEE-crop is
534 suitable for this study since it has been optimized for simulating the phenology and
535 yield of single, early and late rice types grown in China^{23,52}. It has paddy irrigation and
536 soil hydrology schemes²⁴, able to represent the typical irrigation and drainage systems
537 for China's rice fields. It runs in a half-hourly time-step and at 0.5-degree grid cell,
538 suitable for extreme rainfall of short duration, which is a challenging issue for the
539 models running at daily time-step.

540

541 In ORCHIDEE-crop, the rice growth starts from transplanting (LEV), and the growth
542 cycle includes three stages divided by the onset of grain filling (DRP) and the
543 physiological maturity (MAT)⁵². Starting from DRP, the quantity of dry matters
544 accumulated in grains is calculated by applying a progressive "harvest index" to the
545 biomass of the plant. The daily rate of grain increment is proportional to the daily
546 accumulated thermal unit, which could be reduced by frost and extreme heat⁵⁴. The

547 impacts of extreme rainfall are formulated as a factor (α) to reduce the rate of grain
548 increment:

$$549 \quad \alpha = (1 + \Delta EP + \Delta FG), \quad (3a)$$

$$550 \quad \Delta EP = 0.262 \cdot \Delta N_{ut} - 1.644, \quad (3b)$$

$$551 \quad \Delta FG = -0.00424 \cdot KE_{re} - 0.00115 \cdot KE_{ri} + 0.139 \cdot \Delta N_{up} - 3.676, \quad (3c)$$

552 where ΔN_{ut} and ΔN_{up} denote relative change in N uptake per tiller and N uptake per
553 panicle during vegetative phase (%) as a function of soil N losses, respectively. KE_{re}
554 denotes kinetic energy ($\text{J m}^{-2} \text{h}^{-1}$) of the maximum hourly precipitation (exceeding the
555 99th percentile) occurred at 8:00-16:00 in flowering period when spikelets reach
556 anthesis and if hourly air temperature ranges from 23°C to 35°C, ref^{55,56}. KE_{ri} denotes
557 kinetic energy of the maximum hourly precipitation (exceeding the 99th percentile)
558 during ripening phase. Note that Equation 3 summing ΔEP and ΔFG is suitable to
559 diagnose and project extreme rainfall induced ΔY across China, because, according to
560 the nationwide survey ([Supplementary Data 1](#)), the rice planting distances in China (17
561 to 25 cm) are enough to avoid the compensation relationship between EP and FG⁴⁵.
562 Further details on model equations can be found in [Supplementary Table 4](#).

563

564 *Historical simulation.* Two sets of historical simulations were performed for three rice
565 types over China: (1) the comprehensive simulation (S0) that accounts both impacts of
566 rainfall-induced physical disturbance and soil N losses on rice yield and (2) the partial
567 simulation (S1) that only accounts the impact of physical disturbance. By comparing
568 S0 and S1, we could isolate the impact of soil N losses. The difference between yield

569 simulations from the improved and original models can be attributed to the historical
570 extreme rainfall ([Supplementary Data 2](#)), thus we derived ΔY as below:

$$571 \quad \Delta Y = \frac{\text{Yield (improved model)} - \text{Yield (original model)}}{\text{Yield (original model)}} \times 100\%. \quad (4)$$

572 Details on historical input data can be found in [Supplementary Table 6](#). Specifically, we
573 used field observed rice phenology from the CMA to interpolate 0.1-degree
574 transplanting date⁵². We used the satellite-based gridded precipitation datasets (GPM
575 IMERGv6) to quantify extreme rainfall intensities and event amounts, since it is well
576 represented at the site scale ([Supplementary Fig. 16](#)).

577

578 *Future projections.* To evaluate the implications of our new findings for future rice yield
579 projections over China, we applied the improved ORCHIDEE-crop to simulate yield
580 changes of three rice types under RCP 4.5 and 8.5 with present-day agricultural
581 management practices ([Supplementary Data 2](#)). To analyze the effect of future extreme
582 rainfall on rice yield, we estimated additional rice yield loss as the difference in future
583 projected yields between the improved and original model versions in 2085-2100
584 relative to the historical yield simulated by the original model in 2001-2016. To remove
585 systematic deviations of the simulated historical climate, we applied the trend-
586 preserving bias-correction⁵⁷ to the IPSL projected climate change³⁰. The bias correction
587 was then applied to the climate forcing data and extreme rainfall indices during 2085-
588 2100. Further details on input data source for future projections can be found in
589 [Supplementary Table 6](#).

590

591 **Data availability:** The data from the national agrometeorological observation network
592 and the rainfall manipulative experiments are available in [Supplementary Data 1](#).
593 Model input data for historical simulations and future projections are available from
594 public data depositories listed in [Supplementary Table 6](#). Model output data for
595 historical simulations and future projections are available in [Supplementary Data 2](#).

596

597 **Code availability:** Source codes for data analyses are available from
598 <https://figshare.com/s/2ab948dda43e73da44b5> (a link for the review but for the public
599 when being accepted). Source codes for process-based model are available from
600 <http://forge.ipsl.jussieu.fr/orchidee>, under the French Free Software license, compatible
601 with the GNU GPL (<http://cecill.info/licences.en.html>).

602

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772 **Acknowledgements**

773 This study was supported by the National Natural Science Foundation of China
774 (41977082, F.Z.; 42007079, J.F.; 42171096, X.H.W.; 41530528, S.L.P). We
775 acknowledge Kaiwen Liu, Sheng Wang, Wulahati Adalibieke, Yan Bo, Changxian Wu,
776 Wenjun Jiang, Jianping Wang, Lanying Shu, Xinyi Huang, Lian Chen, Daoheng
777 Zhuang, Chunshan Li, Meishuai Yuan, Hongwei Cai, Chengjie Wang for supporting
778 field experiments and laboratory analyses. We acknowledge the CMA for nationwide
779 observations of rice yield, phenology, hourly precipitation, and extreme climate events,
780 the NASA for GPM IMERGv6 data.

781

782 **Author contributions**

783 F.Z. designed the study. Y.W.J., J.F. and X.H.W. performed all computational analyses.
784 F.Z., X.H.W., J.F. and Y.W.J. drafted the paper. L.L. provided high-resolution climate
785 projection using the IPSL model. All co-authors reviewed and commented on the
786 manuscript.

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788 **Competing interests**

789 The authors declare no competing interests.