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1 **Management outweighs climate change on affecting length of rice growing period for**
2 **early rice and single rice in China during 1991-2012**

3 Xuhui Wang^{1, 2, 3}, Philippe Ciais², Laurent Li³, Francois Ruget⁴, Nicolas Vuichard², Nicolas
4 Viovy², Feng Zhou¹, Jinfeng Chang⁵, Xiuchen Wu², Hongfang Zhao¹, Shilong Piao¹

5
6 ¹ Sino-French Institute for Earth System Science, College of Urban and Environmental
7 Sciences, Peking University, Beijing 100871, China

8 ² Laboratoire des Sciences du Climat et de l'Environnement, CEA CNRS UVSQ,
9 Gif-sur-Yvette 91191, France

10 ³ Laboratoire de Meteorologie Dynamique, UPMC/CNRS, IPSL, Paris 75005, France

11 ⁴ Modelling agricultural and hydrological systems in the Mediterranean environment
12 Research Unit, INRA, Avignon 84914, France

13 ⁵ Sorbonne University UPMC-CNRS-IRD-MNHN, LOCEAN/IPSL, Paris 75005, France

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21 **Corresponding author:**

22 Xuhui Wang (xuhui.wang@pku.edu.cn) or Shilong Piao (slpiao@pku.edu.cn)

23 Tel: 86-10-6276-5578, Fax: 86-10-6275-6560

24 **Abstract**

25 Whether crop phenology changes are caused by change in managements or by climate change
26 belongs to the category of problems known as detection-attribution. Three type of rice (early,
27 late and single rice) in China show an average increase in Length of Growing Period (LGP)
28 during 1991-2012: 1.0 ± 4.8 day/decade (\pm standard deviation across sites) for early rice,
29 0.2 ± 4.5 day/decade for late rice and 2.0 ± 6.0 day/decade for single rice, based on observations
30 from 141 long-term monitoring stations. Positive LGP trends are widespread, but only
31 significant ($P < 0.05$) at 25% of early rice, 22% of late rice and 38% of single rice sites. We
32 developed a Bayes-based optimization algorithm, and optimized five parameters controlling
33 phenological development in a process-based crop model (ORCHIDEE-crop) for
34 discriminating effects of managements from those of climate change on rice LGP. The results
35 from the optimized ORCHIDEE-crop model suggest that climate change has an effect on LGP
36 trends dependent on rice types. Climate trends have shortened LGP of early rice (-2.0 ± 5.0
37 day/decade), lengthened LGP of late rice (1.1 ± 5.4 day/decade) and have little impacts on LGP
38 of single rice (-0.4 ± 5.4 day/decade). ORCHIDEE-crop simulations further show that change
39 in transplanting date caused widespread LGP change only for early rice sites, offsetting 65%
40 of climate change induced LGP shortening. The primary drivers of LGP change are thus
41 different among the three types of rice. Management are predominant driver of LGP change
42 for early and single rice. This study shows that complex regional variations of LGP can be
43 reproduced with an optimized crop model. We further suggest that better documenting
44 observational error and management practices can help reduce large uncertainties existed in
45 attribution of LGP change, and future rice crop modeling in global/regional scales should

- 46 consider different types of rice and variable transplanting dates in order to better account
- 47 impacts of management and climate change.
- 48

49 **1. Introduction**

50 The Length of the Growing Period (LGP), defined as the interval in days from the day of
51 planting/transplanting to the day of maturity, is an integrated indicator of crop development
52 that has been related to production (Bassu *et al.*, 2014, Zhang & Tao, 2013). Shortening LGP
53 caused by warmer climate is recognized as a key emerging response through which climate
54 change may impact agricultural production (Bassu *et al.*, 2014, Estrella *et al.*, 2007, Lin *et al.*,
55 2005, Porter *et al.*, 2014). However, historical change in LGP has been reported diversely
56 across different crops and regions. Some studies found shortening LGP over the past decades
57 (Chmielewski *et al.*, 2004, He *et al.*, 2015, Siebert & Ewert, 2012, Tao *et al.*, 2014b, Xiao *et*
58 *al.*, 2013). For example, oat in Germany was found to have shorter LGP over the past five
59 decade with rates of change ranging from -0.1 to -0.4 day/decade (Siebert & Ewert, 2012). On
60 the other hand, there are also studies finding little change or even a lengthening in LGP (Liu
61 *et al.*, 2012, Liu *et al.*, 2010, Sacks & Kucharik, 2011, Tao *et al.*, 2013, Zhang *et al.*, 2013).
62 For example, maize in the US Corn Belt shows lengthening LGP during 1981-2005 with an
63 average positive trend of 5 day/decade (Sacks & Kucharik, 2011).

64
65 The LGP change of China's rice (*Oryza sativa*), which is the staple food resource for
66 more than half of Chinese population and the crop with the largest growing area in the country,
67 has attracted research interest. Observed trends of rice LGP across different stations vary
68 largely from -2 day/decade to more than 7 day/decade over the past 2-3 decades, the majority
69 of the field-scale observations showing either non-significant change or a lengthening of LGP
70 (Liu *et al.*, 2010, Tao *et al.*, 2006, Tao *et al.*, 2013). One hypothesis explaining the lack of

71 evidence for shortening trend of rice LGP was that management practices has counterbalanced
72 the effects of climate change (e.g. Liu *et al.*, 2012, Tao *et al.*, 2013, Zhang *et al.*, 2013).
73 However, large uncertainties remain on the relative contributions of climate change, shifts in
74 transplanting date and other management practices (e.g. use of longer-duration cultivar),
75 which limits our ability to understand the past trends and project the near term evolution of
76 LGP and its possible consequences for future crop production.

77

78 Attribution of the observed trend of LGP from past observations remains challenging
79 because both changes in climate and in management practices have taken place
80 simultaneously. Recent studies used statistical models to characterize the interannual
81 sensitivity of rice LGP to temperature and to separate the contribution of the temperature
82 trend to LGP trend for rice and maize crops over the period 1981-2009 (Tao *et al.*, 2014a, Tao
83 *et al.*, 2013, Zhang *et al.*, 2013). This approach has some limitations: first, statistical models
84 built from interannual LGP variations cannot isolate the impact of changing planting dates
85 from the effects of climate change; second, statistical analyses usually assume linear and
86 constant response to climatic variations (Zhang *et al.*, 2013), but several studies showed that
87 the response is neither linear (Lobell *et al.*, 2013) nor constant with time (Lobell *et al.*, 2014;
88 Burke & Emerick, 2015). On the other hand, crop models can provide an alternative mean to
89 further understand mechanisms and quantify the attributions of different drivers (e.g. Lobell *et*
90 *al.*, 2012). Therefore, a question to ask in complement of the statistical models is whether
91 crop models can be used as an independent method to separate climate change impacts from
92 management. Using crop models factorial simulations where each driver is varied at a time, or

93 combined, instead of statistical models based on historical data can overcome the limitations
94 by having mechanistic representation of climate change impacts (Gregory & Marshall,
95 2012), but earlier application of crop models for the attribution of rice LGP trends were
96 criticized for lack of validation for the study region (Tao *et al.*, 2013).

97

98 The first objective of this study is to optimize a process-based crop model to represent
99 rice phenology in China. The second objective is to run the optimized model for attributing
100 LGP change to climate change and change in various management practices during the last
101 two decades. To achieve these goals, we first collected and harmonized observations of the
102 rice LGP during 1991-2012 from an extensive station network in China (287 sites). Then, a
103 random set of 80% of the sites is used to optimize the process-based crop model
104 (ORCHIDEE-crop) under a Bayesian framework, by calibration of the parameters controlling
105 rice phenology. The optimized model results are then evaluated against the remaining 20% of
106 the site observations. Finally, contributions to LGP trends from climate change, transplanting
107 date change and other management practices (including cultivar change) are separated by
108 comparing the LGP observations and simulations of the optimized model driven by observed
109 and fixed transplanting date.

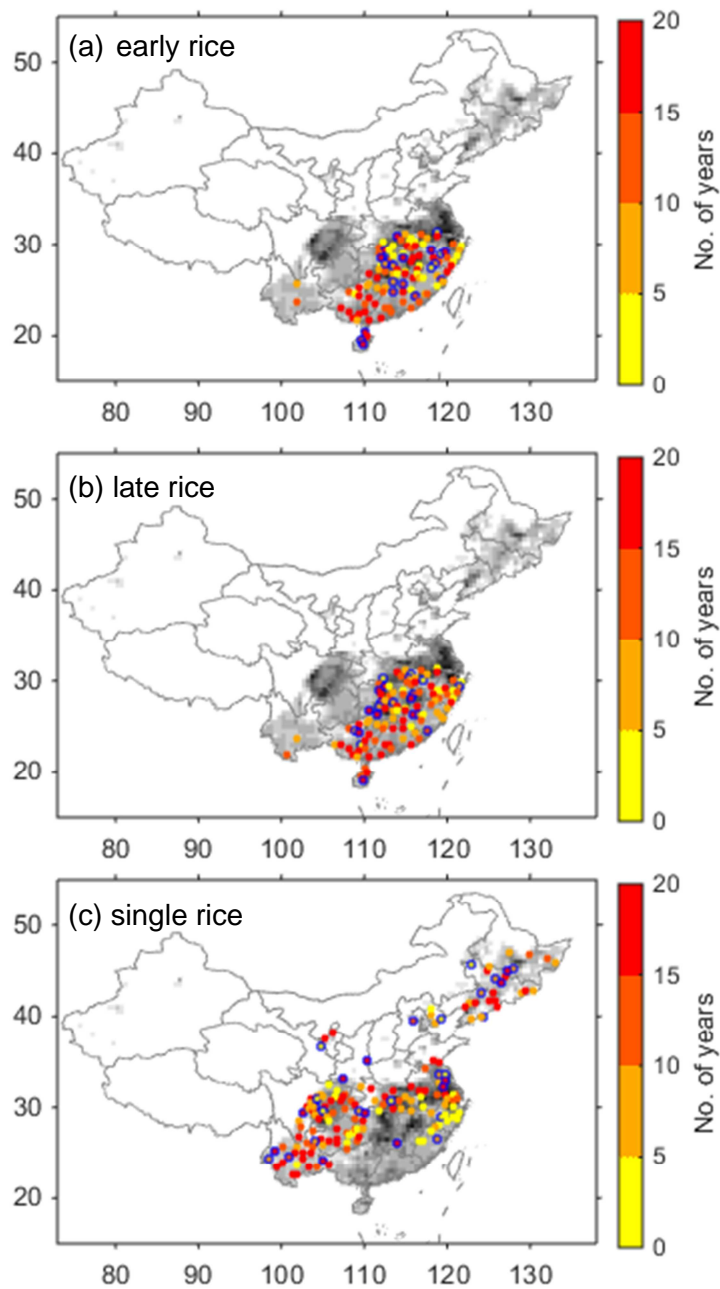
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111 **2. Methods**

112 *2.1 Rice phenology observations from Agrometeorological stations*

113 Transplanting and maturity date of rice in China during 1991-2012 were recorded over
114 287 agro-meteorological field stations by the Chinese Meteorological Administration,

115 covering the entire rice growing area, from the northeast to the southwest and Hainan Island
116 (Fig. 1). The length of These observations were made following a standardized protocol
117 across sites (CMA, 1993). The dataset includes single rice (177 stations), early rice (110
118 stations) and late rice (110 stations). Early rice and late rice have the same number of stations
119 because they are two consecutive crops on the same site comprising the double rice cropping
120 system (i.e. rotation between early rice and late rice (Tao et al., 2013)). 80% of the 287
121 stations are used to optimize ORCHIDEE-crop model parameters. Time coverage of the
122 stations ranges from few years to 21 years (Fig. 1) with 141 stations (88 for single rice and 53
123 for early/late rice) having records longer than 15 years, which are the long-term stations used
124 for the detection and attribution of LGP trends (Figure S3).



125

126 **Fig. 1.** *Spatial distribution of agrometeorological stations in China for (a) early rice, (b) late*
 127 *rice, and (c) single rice. Color shows the number of years of available observations in each*
 128 *station. Blue circle indicates stations randomly selected to cross-validate the model. Grey*
 129 *shading indicates the fraction of rice growing area (Frolking et al., 2002) that darker pixel*
 130 *has larger area of rice croplands.*

131

132 2.2 Simulating rice phenology with ORCHIDEE-crop model

133 ORCHIDEE-crop model (svn version no. 2409) is a process-based crop model, which is
134 based on the generic vegetation model ORCHIDEE (Krinner *et al.*, 2005), simulating carbon,
135 water and energy fluxes (e.g. photosynthesis, respiration and evapotranspiration) and includes
136 an agronomical module simulating crop phenology, leaf area dynamics, growth of
137 reproductive organs, carbon allocations and management impacts (Wu *et al.* 2015). The
138 formula for crop phenology, leaf area dynamics, growth of reproductive organs were
139 originated from a generic crop model STICS (Brisson *et al.*, 2003). Compared with
140 ORCHIDEE-STICS (Gervois *et al.*, 2004), an earlier version of the crop model, which
141 chained the ORCHIDEE model with STICS only through leaf area dynamics,
142 ORCHIDEE-crop has a complete coupling between crop growth and physiology of carbon
143 and water exchanges in soil-vegetation-atmosphere continuum. ORCHIDEE-crop calculates
144 thermal unit accumulation, photosynthesis and energy exchange on a half-hourly time step,
145 while leaf area dynamics, carbon allocation and biomass and soil organic carbon change are
146 simulated on a daily time step.

147

148 Like most crop models, the crop growth cycle in ORCHIDEE-crop is divided into several
149 stages with the developments driven by accumulated thermal unit. Since simulation of rice
150 growth starts from transplanting (LEV), the growth cycle is divided into only three phases,
151 which are divided by the onset of grain filling (DRP) and the physiological maturity (MAT).
152 The thermal unit (*gdd*) needed to grow from transplanting to maturity are prescribed

153 parameters (GDD_{LEVDRP} and GDD_{DRPMAT}). Accumulation of thermal unit (gdd) is calculated at
 154 each half-hourly time step following Eq. 1:

$$gdd = f(T) \times \delta_p \times \delta_v \times (\varepsilon \times \min(\delta_n, \delta_w) + 1 - \varepsilon) \quad (Eq. 1)$$

155 Where $f(t)$ is a tri-linear function of temperature (T) following Eq. 2, δ_p (δ_v , δ_n , δ_w) are
 156 crop-specific scalars for photo-period (vernalization, nitrogen, water) regulations respectively.
 157 ε is a scalar parameter describing the sensitivity of the crop to nitrogen and water stress.

$$f(t) = \begin{cases} 0, & t < T_{min} \text{ or } t > T_{max} \\ t - T_{min}, & T_{min} < t < T_{opt} \\ \frac{T_{opt} - T_{min}}{T_{opt} - T_{max}} \times (t - T_{max}), & T_{opt} < t < T_{max} \end{cases} \quad (Eq. 2)$$

158 As described above, temperature change has a first-order control over gdd (Fig. S1).
 159 Therefore, the most important parameters for accumulations of gdd are GDD_{LEVDRP} ,
 160 GDD_{DRPMAT} , T_{min} , T_{opt} and T_{max} (Table 1), which are to be optimized in the parameter
 161 optimization. Details of the regulation scalars can be found in Brisson *et al.* (2008). In our
 162 study, $\delta_v=1$ because transplanted rice require no vernalization to develop; we assumed that
 163 $\delta_n=1$ and $\delta_w = 1$ because 93% of rice cropland in China is irrigated
 164 (<http://www.knowledgebank.irri.org/country-specific/asia/rice-knowledge-for-china/2013-06-03-07-15-17>,
 165 Salmon *et al.*, 2015), and the nitrogen fertilizer application rate is higher than
 166 100 kgN ha⁻¹ (Zhou *et al.*, 2014). In this study, we also assumed $\delta_p=1$, which indicates that
 167 photoperiodic constraint on the phenology is minimal for rice. This is probably true for early
 168 and single rice, because varieties insensitive to day-length change are commonly used (Cao *et*
 169 *al.*, 2011). There are, however, cases for late rice, where day-length sensitive varieties are
 170 used (Cao *et al.*, 2011), but we cannot account it due to lack of information on the extent for
 171 application of day-length sensitive varieties. Further details on ORCHIDEE-crop structure

172 and parameters can be found in Wu et al. (2015). It should be noted that rice phenology
173 development is modelled mostly by temperature driven processes in almost all rice models (Li
174 et al., 2015), so the parameter we chose here represent the main processes driving the
175 phenology development. Other parameters of ORCHIDEE-crop are not optimized here,
176 because the phenology observations can provide loose constraint on them.

177

178 In this study, two types of simulation experiments were performed for each site: (1) For
179 validation and comparison with observed LGP, simulation S0 was driven by observed variable
180 climate and the observed variable transplanting date each year at each station; (2) For
181 isolating the impact of transplanting date from that of climate change on LGP, simulations S1
182 was driven by a time-invariant (fixed) transplanting date defined as the average of the earliest
183 three year of each record. Climate forcing for simulation S0 and S1 was obtained from
184 CRU-NCEP dataset v5.2 (<http://dods.extra.cea.fr/data/p529viov/cruncep/>). The difference
185 between S0 and S1 can be used to attribute the fraction of LGP trends explained by changes in
186 transplanting dates. Assuming the model structure has no time-dependent systematic errors,
187 the residual difference (Δ) between trends in observed LGP and in simulation S0 can be
188 interpreted as reflecting the contribution of all other management operations not considered in
189 S0, including change in the cultivars. Previous studies usually interpreted such a residual
190 between observed and modelled LGP (either from statistical modelling or from process
191 modelling) as being caused by change in the cultivars used over time (Liu et al., 2012, Tao et
192 al., 2013, Zhang et al., 2013), but it could cover other changes in agronomic practice, such as
193 fertilization change.

194

195 2.3 Parameter optimization with particle filter

196 We used a particle filter method with sequential importance resampling (PFSIR) to
197 optimize the ORCHIDEE-crop parameters for early, late and single rice phenology
198 respectively over China. Particle filter is a Monte-Carlo implementation of recursive Bayesian
199 theorem to estimate the posterior probability density of a state-space (here is the parameter set
200 of the model) (van Leeuwen, 2009). A set of ensemble members of the parameter set called
201 “particles” hereafter, are used as a discrete approximation of the multi-dimensional
202 probability density function (PDF) of the model parameters. The PDF evolves by propagating
203 all particles forward in space or time through the ORCHIDEE-crop model. Each step when
204 observations become available, each particle is assigned a weight (or importance) according
205 to the model-observation differences. A new set of particles is generated after each iteration
206 by resampling the weighted particles (sequential importance resampling). The optimized
207 parameter sets for early rice, late rice and single rice are obtained through applying PFSIR to
208 ORCHIDEE-crop model respectively. Particle filters has been found to have broader
209 suitability than traditional variational methods (Chorin & Morzfeld, 2013), in particular for
210 non-linear cases. Thus, variant forms of particle filter have become growingly popular when
211 applying in earth system models (e.g. Billionis *et al.*, 2014, Yu *et al.*, 2014). Further details of
212 PFSIR used in this study can be found in the Appendix.

213

214 Advantages of using the PFSIR method are multiple: First, unlike error minimization
215 methods or manual adjustments previously adopted (e.g. Gregory & Marshall, 2012, Zhang

216 *et al.*, 2014a), PFSIR not only provides a best (maximum likelihood) estimate, given an
217 observation probability, according to the Bayes theorem, but also the uncertainties of the
218 optimized parameters; Second, unlike variational methods (e.g. 4D-Var) assuming Gaussian
219 distributions of the parameters, no assumptions are necessary for the posterior parameter
220 distribution of the parameters in the particle filter, which makes it suitable for a model like
221 ORCHIDEE-crop that uses some non-Gaussian and threshold-like parameters; Third, particle
222 filter does not assume linearity of the state-space, which overcomes some of the limitations of
223 methods based upon linearization of the state-space such as ensemble Kalman filter (van
224 Leeuwen, 2010); Fourth, when being fed with large dataset, the Bayes-based particle filter is
225 less sensitive to data outliers than error minimization methods (e.g. Kersebaum *et al.*, 2015),
226 which also make it suitable for application in crop models and over regional scale; Fifth, the
227 particle filter does not require the effort of constructing the tangent linear model of the
228 original model for calculating sensitivities of the model output to its parameters, and tends to
229 have higher efficiency than other Monte-Carlo methods (Gauchere *et al.*, 2008). The particle
230 filter is thus recommended for non-linear data assimilation, though has limitations for
231 high-dimensional system (van Leeuwen, 2009). With growing number of parameters
232 (dimension of the parameter space), the filter may become less efficient and required a huge
233 number of computing resources in order to obtain satisfactory estimates. Some improvements
234 to the particle filter would be needed in such high-dimensional cases (e.g. van Leeuwen,
235 2010). Given the relatively small dimension of the parameter set (Table 1), this poses little
236 threats to our study.

237

238 To evaluate the robustness of the optimized model, we randomly selected 20% of the sites
239 (22 sites of early rice, 21 sites of late rice and 35 sites of single rice, see Fig. 1 for its spatial
240 distribution) as validation sites. The validation sites are not used into the PFSIR, providing
241 independent evaluation measurements of the performance for the optimized model. It should
242 be noted that the probability of posterior parameter distribution usually reflects the strength of
243 constraint from the observation data, thus the spread of posterior probability distribution is
244 also a metric to evaluate the performance of the particle filter. Larger spread of posterior
245 probability distribution would indicate loose constraint from the observations.

246

247 It should be noted that we infer only one set of optimized parameter for each rice type
248 over China, which is consistent with our intention to use a generic model across large regions,
249 but could be a limitation in cases when local varieties within the same rice type have very
250 different parameters. Separating the rice growing area into finer zones and producing multiple
251 parameter sets for each rice type (Zhang *et al.*, 2014a) may yield smaller errors due to
252 increased degree of freedom and a potentially better calibration reflecting the diversity of
253 local varieties. But doing this would also increase the risk of over-fitting and would require a
254 detailed zoning map of rice crop varieties instead of zoning map of climate. In addition, there
255 are growing requests for assessing climate change impacts over regional and global scales
256 (Rosenzweig *et al.*, 2014) asking for robust parameter sets representing a broad scale of the
257 growing area.

258

259 *2.4 Trend analyses*

260 We calculated the trend of rice LGP from the observations, the simulations S0 and S1,
261 and for the residual Δ by regressing time series of LGP at each station against year using least
262 square regression. The trend estimates were compared with non-parametric test (Sen's slope)
263 (Fig. S2). The similar estimates between least square regression slope and Sen's slope indicate
264 robustness of the trend estimates to potential outliers. Statistical significance was reported
265 based on two-tailed *t*-test. Only stations with more than 15 years of observations during
266 1991-2012 are used in the trend analyses (Fig. S3).

267

268 **3. Results**

269 *3.1 Simulated LGP with prior and posterior parameters*

270 Fig. 2 shows the histogram of the simulated bias of LGP (difference between observed
271 LGP and simulated LGP) for simulation S0 before and after optimization, and for the three
272 rice types. Over site-years used in optimization, the posterior model largely reduces the root
273 mean square error (RMSE) from 32.7 days (prior) to 14.8 days for early rice (optimized) (Fig.
274 2a), from 108.9 days to 12.4 days for late rice (Fig. 2b), and from 73.7 days to 24.4 days for
275 single rice (Fig. 2c). When we only look at spatial variations across sites (Fig. S4), we found
276 that the posterior model not only reduces the absolute errors (indicated by the vicinity to 1:1
277 line), but also better reproduces the spatial LGP gradient among the sites used for
278 optimization. The R^2 for the spatial gradient improves from 0.41 ($P<0.01$) to 0.55 ($P<0.01$)
279 for early rice (Fig. S4a), from 0.00 ($P=0.91$) to 0.33 ($P<0.01$) for late rice (Fig. S4b), and from
280 0.21 ($P<0.01$) to 0.47 ($P<0.01$) for single rice (Fig. A2c). Interannual variations of LGP at the
281 long-term sites used for optimization also show significant improvement for all three rice

282 types ($P < 0.05$) (Fig. S5). These show that given the structure of the ORCHIDEE-crop model,
 283 with the PFSIR optimization method, it is possible to find a set of parameters for each of the
 284 three rice types, which provides an improved fit to the LGP observations across sites and
 285 years.

286

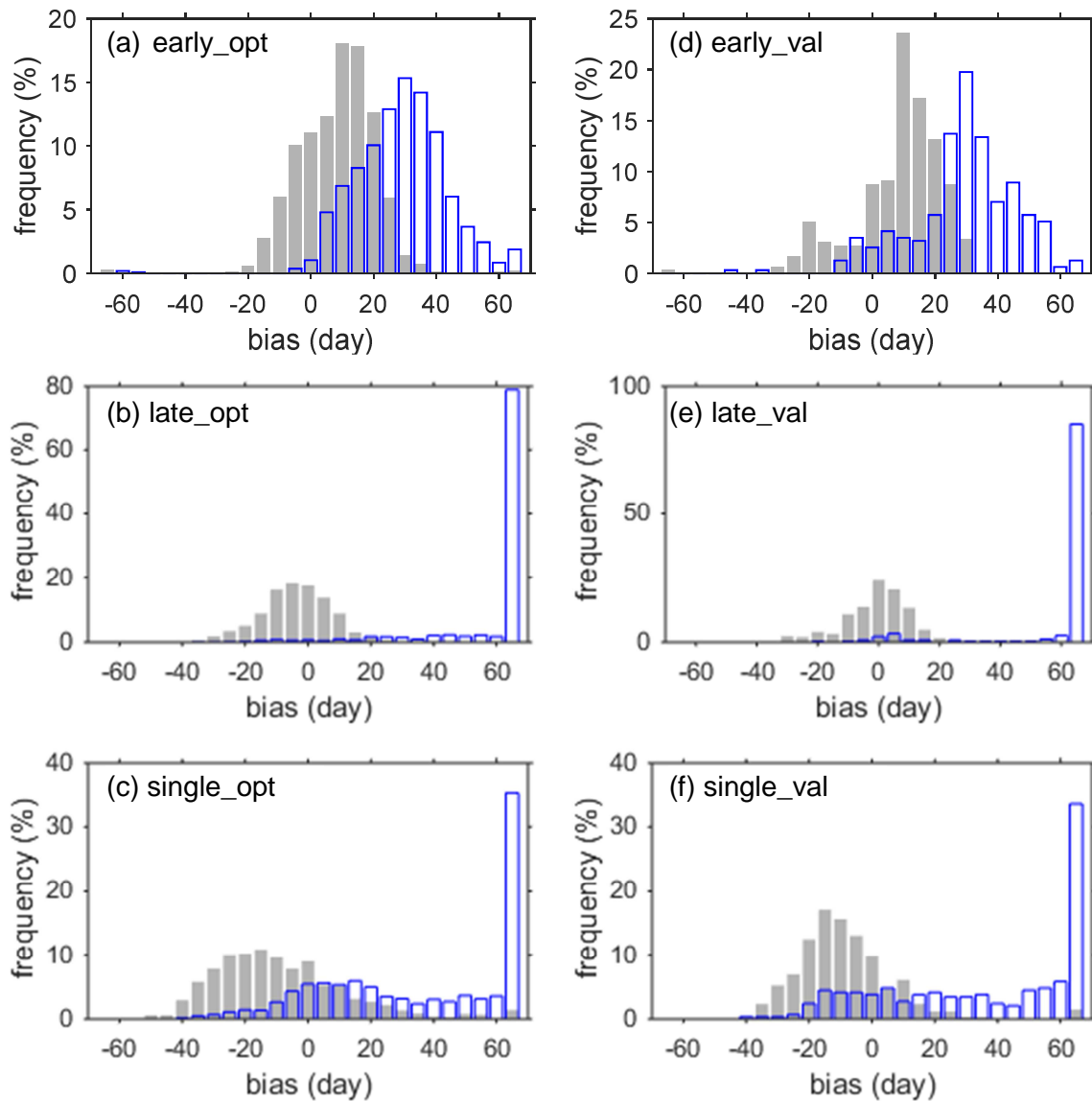
287 To test whether the improvements due to optimization is limited to the sites chosen for
 288 optimization, we also use the prior and posterior model parameters in ORCHIDEE-crop runs
 289 at the cross-validation sites. The RMSE of LGP for the simulation S0 with prior parameters
 290 are 33.9 day for early rice, 113.0 day for late rice and 74.5 day for single rice, respectively.
 291 The RMSE of LGP with posterior parameters at the cross-validation sites are 16.3 day for
 292 early rice, 10.2 for late rice and 19.2 for single rice, which are close to that over the
 293 optimization sites (Fig. 2d-f). Therefore, the RMSE reduction over the validation sites is
 294 similar to that over the optimization sites (Fig. 2d-f). The improved spatial gradients (Fig.
 295 S4d-f) and interannual correlation between observed and modeled LGP (Fig. S5d-f) also hold
 296 for the validation sites. Indeed, when we re-selected the sites used for optimization and
 297 running the particle filter once again for testing, we obtain a similar set of parameter set than
 298 the one presented in Table 1, further indicating the robustness of the optimized models in
 299 reproducing the spatiotemporal variations of rice LGP in China during 1990-2012, for the
 300 three rice types.

301 **Table 1.** Prior and posterior parameters for early rice, late rice and single rice.

Prior		Posterior	
Generic rice	Early rice	Late rice	Single rice

GDD_{LEVDRP}	895 ± 115	860 ± 9	610 ± 12	645 ± 5
GDD_{DRPMAT}	554 ± 115	322 ± 7	345 ± 9	420 ± 6
T_{min}	13.0 ± 4.3	9.9 ± 0.5	9.2 ± 1.1	9.4 ± 0.5
T_{opt}	30.0 ± 4.3	32.3 ± 1.9	23.4 ± 0.6	22.8 ± 0.5
T_{max}	40.0 ± 4.3	36.5 ± 3.6	38.2 ± 1.1	35.7 ± 0.7

302



303

304 **Fig. 2.** Histogram of the differences between observed length of rice growing period (LGP)
305 and simulated LGP with prior parameters (blue-edged bars) and optimized parameters (grey
306 bars) for (a) optimization sites of early rice, (b) optimization sites of late rice, (c) optimization
307 sites of single rice, (d) validation sites of early rice, (e) validation sites of late rice, and (f)
308 validation sites of single rice.

309

310 The optimization of ORCHIDEE-crop parameters not only significantly reduced the
311 misfit with site observations but also significantly changed the simulated trend in LGP (Fig
312 S4). For early and single rice, the trend in optimized LGP (-0.7 ± 2.7 day/decade (mean \pm
313 standard deviation across sites) for early rice and -0.5 ± 5.2 day/decade for single rice) differs
314 by more than 60% ($P < 0.01$) from the prior modeled LGP trend (-1.7 ± 4.8 day/decade for early
315 rice and -1.5 ± 18.4 day/decade for single rice)(Fig. S6a and c). For late rice, the optimization
316 even changes the sign of the simulated LGP trend and largely reduced the spatial variations of
317 the trend (Fig. S6b). The average LGP trend for late rice is changed from -7.5 ± 16.7
318 day/decade to 1.0 ± 3.0 day/decade (Fig. S6b). The optimized model thus produces lengthening
319 instead of shortening LGP for late rice. The LGP trend simulated by the optimized model is
320 further analyzed in the section “*attribution of LGP trends to climate change, transplanting*
321 *date change and other management factors*”.

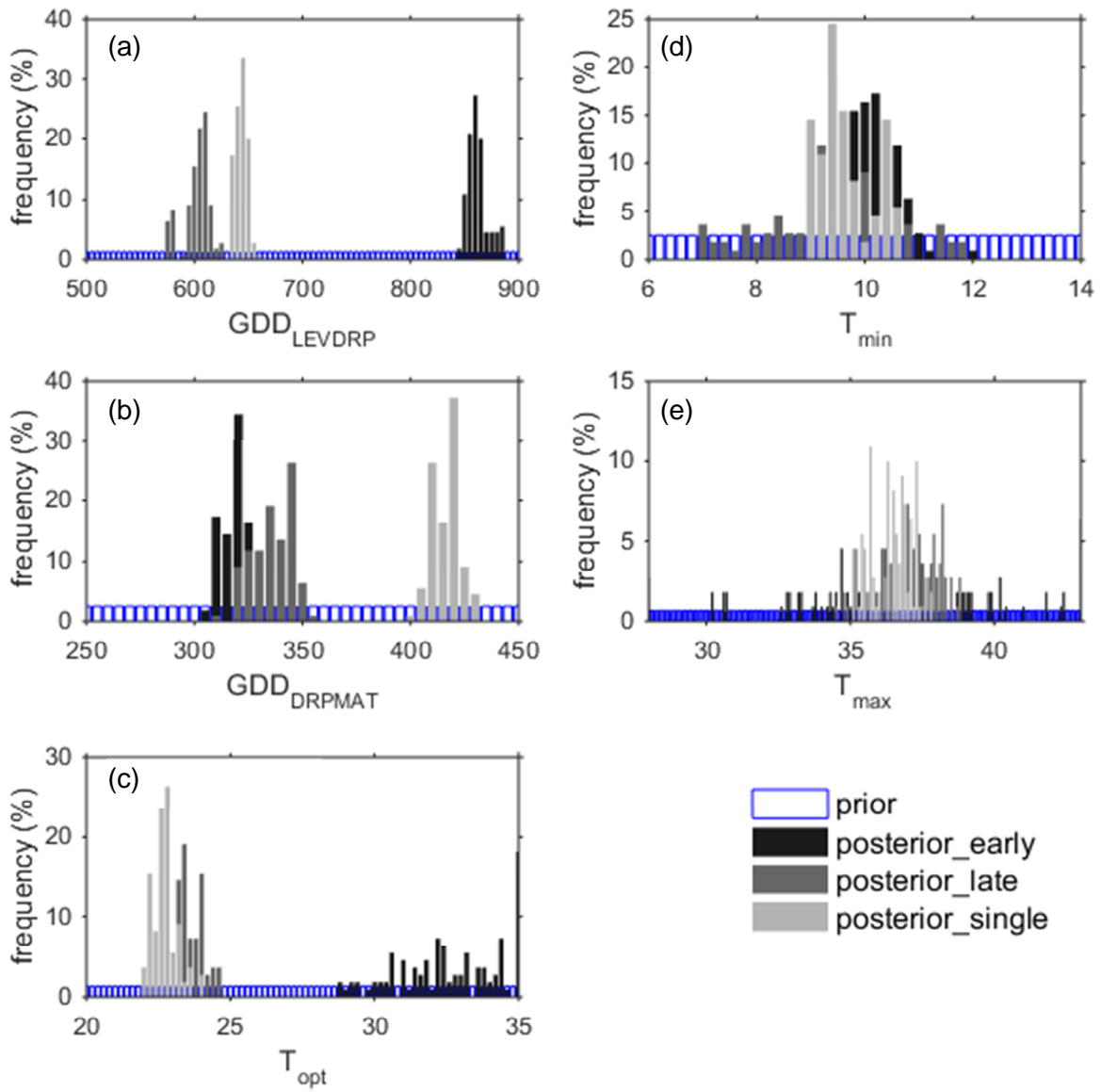
322

323 3.2 Optimized parameter sets

324 Fig. 3 shows the probability distribution of the five optimized parameters (see Methods
325 section for descriptions of the parameters) of the ORCHIDEE-crop simulation for LGP before

326 (prior) and after (posterior) optimization for early rice, late rice and single rice, respectively.
327 Optimized (posterior) parameters of thermal unit requirements (GDD_{LEVDRP} and GDD_{DRPMAT})
328 show largest uncertainty reduction (UR) with a 90% error reduction in the standard deviation
329 after optimization (Fig. 3a and b, Table 1), indicating strong observational constraints on these
330 parameter values. Early, late and single rice have their posterior thermal unit requirements
331 (GDD_{LEVDRP} and GDD_{DRPMAT}) concentrated in a narrow range of values, which are
332 significantly different from each other ($P < 0.05$). On the other hand, the temperature threshold
333 parameters regulating phenological development (T_{min} , T_{opt} , and T_{max} in Eq. 2) show different
334 values after optimization among the three rice types. For early rice, T_{min} for phenology
335 development is well constrained with a UR of 78% (9.9 ± 0.5 °C, Fig. 3d), while T_{opt} has a
336 large posterior range between 29 °C and 35 °C (32.3 ± 1.9 °C, Fig. 3c) and a UR of 55%. For
337 late and single rice, optimized T_{min} are slightly lower than early rice (9.2 ± 1.1 °C for late rice
338 and 9.4 ± 0.5 °C for single rice, Fig. 3d) and UR of 52% and 78%. On the contrary, optimized
339 T_{opt} for late and single rice are much lower than early rice (23.4 ± 0.6 °C for late rice and 22.8
340 ± 0.5 °C for single rice, Fig. 3c) with UR ~85%. The higher optimal T_{opt} and T_{min} values
341 found for early rice, compared to single and late rice suggest that early rice must be more
342 acclimated to the high temperature in spring and summer over southern China, which matches
343 its geographical distributions (Fig. 1) and was not accounted in the prior values of these
344 parameters. For all the three rice types, the posterior probability distribution of T_{max} shows a
345 large range (Fig. 3e) indicating that this temperature threshold that corresponds to the stop of
346 phenology development is less well constrained from the LGP observations, likely because
347 T_{max} is a high-end threshold, which is not frequently reached in the historical period

348 1991-2012 (4 site-days for early rice, no site-day for late rice and 7 site-days for single rice).



349

350 **Fig. 3.** Histogram of the prior and posterior parameter distribution for early rice, late rice

351 and single rice. The optimized parameters include (a) GDD_{LEVDRP} , (b) GDD_{DRPMAT} , (c) T_{opt} , (d)

352 T_{min} , and (e) T_{max} (see Methods section for definitions and descriptions of the parameters).

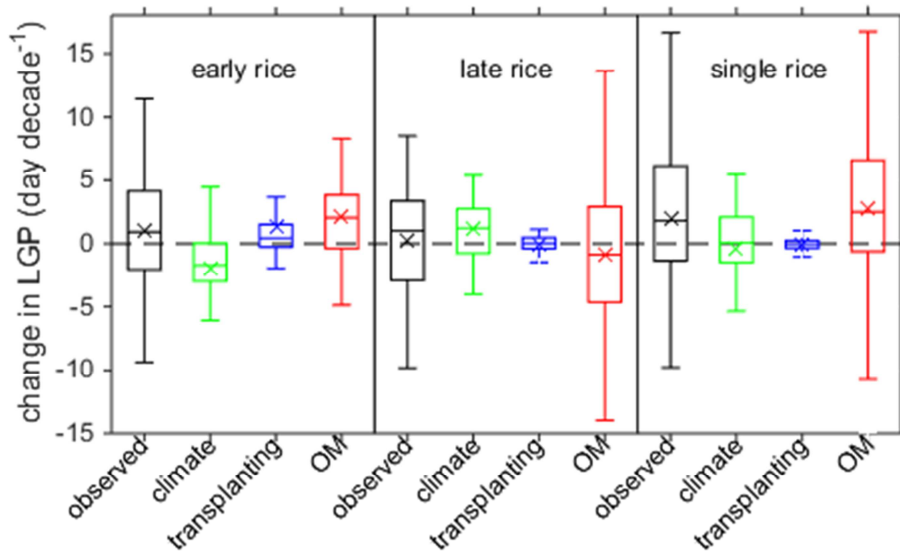
353

354 3.3 Attribution of LGP trends to climate change, transplanting date change and other

355 *management factors*

356 At country scale, observations show an average lengthening of LGP for all three types of
357 rice (Fig. 4). Single rice sites show the largest lengthening rate of 2.0 ± 6.0 day/decade (mean \pm
358 standard deviation in spatial variations), followed by early rice (1.0 ± 4.8 day/decade) and late
359 rice (0.2 ± 4.5 day/decade). But there are large site-to-site variations in the observed LGP trend
360 (Fig. S7). For single rice, 61% of the sites show a trend towards longer LGP, 50% of which
361 are statistically significant (Fig. s7c). For early and late rice, the percentage of sites showing
362 longer LGP is similar (58% and 55% for early and late rice respectively), but the percentage
363 of significant positive trends was smaller than that for single rice (27% and 19% for early and
364 late rice respectively). There is a large proportion of sites showing no significant change of
365 LGP (more than 50% for all three types of rice), indicating that LGP change is either weakly
366 sensitive to climate change or compensated by effects of change in climate and managements.
367 To further understand the drivers of the LGP trends, we estimated the contribution of climate
368 change alone from simulation S1, the contribution of transplanting date from the difference
369 between simulation S0 and S1, and interpreted the contribution of all other management (OM)
370 as being caused by a non-modeled residual term Δ , as explained in the Method section.

371



372 **Fig. 4.** Box plot of change in the length of rice growing period length (LGP) over the past two
 373 decades derived from observations and simulations for the three rice types. The LGP change
 374 due to climate change is obtained from simulation S1; The LGP change due to change of
 375 transplanting date is obtained by the difference between simulation S0 and simulation S1; The
 376 LGP change due to other management (OM) is obtained by the difference between
 377 observations and simulation S0. The lower and upper edge of the box indicate 25th and 75th
 378 percentile of the trends. The line and cross inside the box indicate the median and the mean of
 379 the trends, respectively.

380

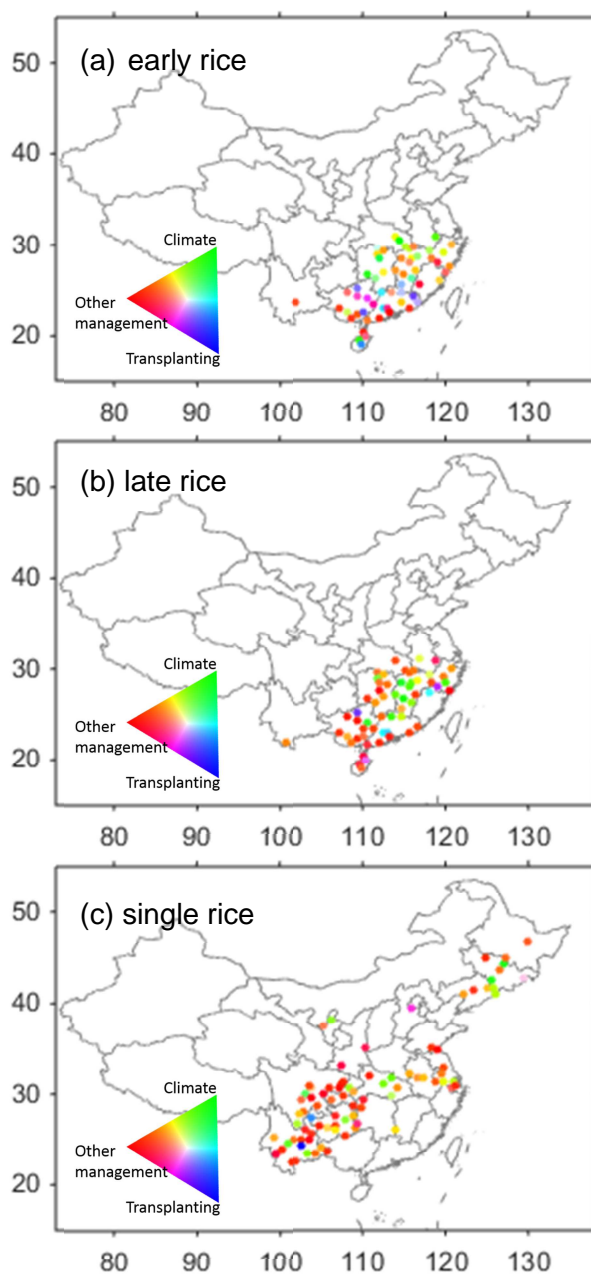
381 As Fig. 4 and Fig. 5 shows, the impacts of climate change on LGP change differs between
 382 the three rice types. For early rice sites using the simulation S1 with the optimized model, we
 383 infer an average shortening of LGP induced by climate change alone of -2.0 ± 5.0 day/decade
 384 (Fig. 4). Except for sites in Hainan and Guangxi, the shortening of LGP in simulation S1 is
 385 widespread (71%) and significant at 41% of the early rice sites (Fig. S7j). However, for late
 386 rice, climate change alone leads to an average lengthening of the LGP of 1.1 ± 5.4 day/decade,

387 with 16% of the sites having a significant lengthening mostly in Hunan, Jiangxi and Fujian
388 provinces (Fig. S7k). This positive LGP trend for late rice in response to climate change
389 occurs in ORCHIDEE-crop because temperature during the growing season is reaching the
390 optimum temperature of phenology development for late rice in southern China (Table 1). For
391 single rice, the contribution of climate change to LGP trends shows regional differences.
392 Climate change is modeled to shorten LGP over northeastern China and high-altitude Yungui
393 plateau over southwestern China, but to lengthen LGP in the middle and lower reach of
394 Yangtze River basin (Fig. S7l). These regional contrasts for single rice LGP trends leads to a
395 near neutral average impact of climate change on LGP trend across China (-0.4 ± 5.4
396 day/decade, Fig. 4). Among all the sites, climate change is the dominant factor contributing to
397 the observed LGP trend for 26% of early rice sites, 28% of late rice sites and 19% of single
398 rice sites (Fig. 5).

399

400 We found that 66% of the early rice sites experienced earlier transplanting date during
401 1991-2012 (Fig. S8). From the difference between modeled LGP in simulation S0 and S1, we
402 infer that the earlier shift of the transplanting date (-2.0 ± 4.8 day/decade) alone, has
403 lengthened the LGP of early rice by 1.3 ± 5.5 day/decade (Fig. 4). But earlier transplanting
404 practice have not been adopted widely for late rice and single rice sites, and the observation
405 sites showing positive and negative trends in transplanting dates are of similar proportion for
406 late rice and single rice (Fig. S8b and c). The magnitude of the average trend in transplanting
407 date is also small for these two types of rice (-0.3 ± 3.4 day/decade for late rice and 0.1 ± 4.1
408 day/decade for single rice), which has minor impacts on the simulated LGP change in the

409 S0-S1 difference (-0.1 ± 5.0 day/decade for late rice and -0.1 ± 1.7 day/decade for single rice,
410 Fig. 4). Therefore, the earlier shift of transplanting date is the dominant factor contributing to
411 the trend of LGP at 17% of early rice sites (Fig. 5a), and a minor driver of LGP trends for
412 other rice types, being dominant at only 7% of the late rice sites (Fig. 5b) and 2% of the single
413 rice sites (Fig. 5c).



415 **Fig. 5.** *Spatial distribution of the controlling factors on change in the length of growing*
416 *period (LGP) for (a) early rice, (b) late rice, and (c) single rice. Green color indicates LGP*
417 *change is primarily driven by climate change, blue color indicates LGP change is primarily*
418 *driven by transplanting date change, and red color indicates LGP change is primarily driven*
419 *by other management. Intermediate colors indicate co-dominance by more than one factor.*

420

421 On average across sites, the role of other management practices (OM), inferred from the
422 residual trend not explained by transplanting date and climate change, is found to be the
423 predominant factor for LGP change for early and single rice. OM are identified to be
424 responsible for a lengthening of LGP by 2.1 ± 3.9 day/decade for early rice and 2.8 ± 7.6
425 day/decade for single rice (Fig. 4). A great majority of the early rice sites (71%) and single
426 rice sites (64%) show positive contributions of OM trends. Over 20% of early rice sites and
427 27% of single rice sites, the OM induced LGP trend is statistically significant ($P < 0.05$, Fig.
428 S7d-f). On the contrary, OM contributes to a shortening of LGP for late rice by -0.8 ± 5.8
429 day/decade (Fig. 4), with a significant LGP shortening in Hunan, Jiangxi, Guangdong and
430 Fujian provinces (Fig. S7e). The dominant role of OM is prevalent in southern China
431 provinces, such as Guangdong, Guangxi and Yunnan for both early rice and late rice (Fig.
432 5a-b). For single rice sites, OM is the predominant driver of the LGP trend from the northeast
433 to the southwest at 78% of the sites (Fig. 5c).

434

435 **4. Discussion**

436 Our analyses of a large network of rice phenological observations with more than 100

437 long-term stations across rice growing area in China indicate that the LGP of single rice has
438 become longer over the past two decades, which is consistent with a recent study focused on
439 Northeast China and Yangtze River basin during 1980-2009 (Tao *et al.*, 2013). Although
440 site-to-site variations are large, all three rice types exhibit an average trend towards longer
441 LGP. The ORCHIDEE-crop model optimized upon observed LGP was run using factorial
442 simulations, with either climatological (fixed) or observed transplanting dates, and variable
443 climate. The results suggest that the primary factors driving the LGP trends are not the same
444 among the three rice types.

445
446 We found that recent climate change considered as a single driver in the model, shortened
447 the LGP of early rice (Fig. 4 & Fig. S7j), which is consistent with previous statistical
448 modelling (Zhang *et al.*, 2013) and process modeling based on four sites (Liu *et al.*, 2012).
449 For late rice, climate change appears to have induced little change or a lengthening of LGP,
450 which is different from early rice (Liu *et al.*, 2012, Tao *et al.*, 2013) and from some other
451 temperate crops (Lobell *et al.*, 2012). This is because the optimized parameter values indicate
452 a lower optimum temperature (23.4 ± 0.6 °C) for phenology development of late rice than for
453 early rice. Late rice sites are mainly located in southern China where temperature after
454 transplanting (around July and August) is higher than this optimal temperature of phenology
455 development of late rice (Li *et al.*, 2010). Thus, further warming beyond the temperature
456 optimum will not accelerate the phenology development and cause a lengthening of LGP (Fig.
457 S1, Yin, 1994). It should be noted that the optimum temperature that we determined from
458 PFSIR is consistent with statistical analyses of rice phenology observations in southern China

459 (Xie *et al.*, 2008) and with the incubation study (Summerfield *et al.*, 1992), but lower than
460 that used in previous models (Liu *et al.*, 2012, Zhang *et al.*, 2014b), parameters of which may
461 have originally derived from earlier studies based on assumptions or rice varieties in
462 Southeast Asia (e.g. Kropff *et al.*, 1993). Our capability to further assess this parameter is
463 rather limited since field trials determining the optimum temperature of phenology
464 development are rarely available, requiring more data and future studies to refine this key
465 parameter in order to more accurately project climate change impacts on LGP change. It
466 should also be noted that, although high temperature stress did not necessarily shorten LGP, it
467 may still adversely affect rice yields as it stresses photosynthesis (Yin & Struik, 2009), and
468 thus reduce biomass accumulation for the harvest.

469

470 By comparing the simulations driven by fixed transplanting dates (S1) and by variable
471 transplanting dates (S0), we can separate the contribution of transplanting date trends on LGP
472 trends. Although an earlier transplanting date is a pragmatic autonomous adaptation through
473 which farmers adapt to climate change (Olesen *et al.*, 2011), its effect on the regional trends
474 of LGP was not separated by previous statistical models (Tao *et al.*, 2013, Zhang *et al.*, 2013),
475 probably due to its co-variations with climate (Tao *et al.*, 2006). It may also be related with
476 the linear assumption of previous statistical analyses (e.g. Tao *et al.*, 2013; Zhang *et al.*, 2013),
477 which can be improved using recent progresses in statistical analyses including non-linear or
478 threshold like equation (e.g. Burke & Emerick, 2015; Solomon, 2016). We found that changes
479 in transplanting date were widespread over the last 20 years for early rice sites in southern
480 China, and that they contributed to lengthen LGP, whereas climate change has the opposing

481 effect of shortening LGP. This suggests that the adoption of earlier transplanting date has
482 partly mitigated climate change impacts on early rice growth over the past two decades.
483 However, the same adaptation strategy is probably not possible for late rice because earlier
484 transplanting and lengthening of LGP nearly compensate for each other for early rice, leaving
485 no more time during the season available for earlier transplanting of late rice (MOA, 2014). In
486 addition, advancing transplanting dates for late rice to mitigate climate change will have
487 limitation due to frost risk and photo-period constraints in the autumn. The same reason may
488 also explain why single rice sites show large site-to-site variations on the sign of change in
489 transplanting date (Fig. S8).

490

491 Other management practices were found to be the dominant driver of LGP trends for
492 early rice and single rice across the country (Fig. 5), which is about one magnitude larger than
493 the contribution of transplanting date and climate trends for early rice and single rice, though
494 with large site-to-site variations (Fig. 4). Previous studies usually interpreted this residual
495 contribution not explained by climate change as the contribution of cultivar change, in
496 particular the adoption of long-duration cultivars (Liu *et al.*, 2012, Tao *et al.*, 2013, Zhang *et*
497 *al.*, 2013), which was supported by the empirical assessment of change in thermal
498 requirements (Zhang *et al.*, 2014b). This hypothesis is reasonable, since use of
499 longer-duration cultivars is one of the most commonly used practices to achieve higher yields
500 and mitigate the impacts of climate change (Aggarwal & Mall, 2002, Porter *et al.*, 2014).
501 However, there are other management practices that could also impact LGP trends. For
502 example, foliage nitrogen fertilizer spraying on leaf in the late growing season, can also lead

503 to increase of leaf longevity and the growing season (Russell *et al.*, 1990). Future studies
504 should account for these effects with spatially and temporally explicit datasets in order to
505 more accurately attribute and project LGP change. In addition, OM trends may not necessarily
506 induce longer LGP. Local agronomists in China have been studying and recommending the
507 combination of rice varieties with shorter-duration and longer-duration cultivars in order to
508 improve yield and to minimize risk of exposure to climate extremes (e.g. Ai *et al.*, 2010; Mao
509 *et al.*, 2015; Li *et al.*, 2016) Shorter-LGP induced by OM seems to be widespread for late rice
510 in southern China. These efforts were taken likely because shorter LGP for late rice can have
511 the advantage to avoid the damage induced by cold weather events during anthesis and grain
512 filling, known as the “cold dew wind” (Huo & Wang, 2009, Wu *et al.*, 2014). The risk of
513 late rice exposure to cold damage can be more than 30% for some regions in southern China
514 according to (Wu *et al.*, 2014), and warming over past decades does not alleviate the risk of
515 the weather events and reduce late rice production when it occurs (Huo & Wang, 2009,
516 Ministry Of Agriculture, 2014).

517

518 Unlike previous studies identifying climate change as the dominant driver of rice
519 phenology change, using field trials (De Vries *et al.*, 2011), statistical models (Zhang *et al.*,
520 2013) or crop model simulation (Yao *et al.*, 2007), our analyses combining phenology
521 observations and optimized crop model simulations indicate that management practices
522 (including both change in transplanting date and changes of OM) probably outweigh the
523 impact of climate change on LGP change for early rice and single rice in China during the
524 past two decades. However, we are only able to separate the effects on LGP trends of trends

525 transplanting date from other management practices, such as cultivar change, due to limited
526 data on spatio-temporal variations of other management practices. On the other hand,
527 attribution of LGP trends to OM has the largest uncertainty in this analysis since the role of
528 OM is inferred from the misfit of model runs driven by climate change and observed
529 transplanting date and the observations. Errors in the attribution of LGP trends to climate or
530 transplant date trends, depends largely on the crop model used, a structural bias in this model,
531 and non-unified observational error across sites and years will translate into an erroneous
532 attribution to OM. Through the Bayesian optimization framework (particle filter with
533 sequential importance resampling), we optimized the ORCHIDEE-crop model to fit the
534 spatio-temporal variations of LGP for the three rice types across China. The optimized model
535 not only can reproduce the phenology of the sites used for optimization, but also remains
536 robust when applied to validation sites (Fig. 3). Therefore, the optimized model provides
537 some confidence in the attribution, compared to models not optimized for rice croplands in
538 China (e.g. Liu *et al.*, 2012). Indeed, the posterior model largely differs from the prior model
539 in the estimated climate change impacts on LGP change (Fig. S6), further highlighting the
540 necessity of optimizing crop models for regional studies. Admittedly, the optimized model
541 simulations still cannot perfectly reproduce spatiotemporal variations in LGP, which may
542 introduce uncertainties in the attribution of LGP trends to climate trends, but this should not
543 largely impact our conclusions because we found no significant correlation between trend in
544 the residual LGP (difference between observations and simulation S0) and the trend in
545 growing season temperature (Fig. S9). This indicates that the trend attributed to OM is
546 probably not biased by climate trend unexplained by ORCHIDEE-crop. On the other hand, in

547 addition to optimizing the parameters of a single model against observations to reduce
548 parameter uncertainties, recent studies indicate that multiple models can perform better than
549 one model (Li *et al.*, 2015, Martre *et al.*, 2015), due to the consideration of structural
550 uncertainties. Although there are many difficulties in coordinating multiple models, promising
551 future studies using model ensembles with the same protocol can improve our understanding
552 regarding the structural uncertainties (e.g. Elliott *et al.*, 2015). It should also be noted that
553 almost all current rice models, including ORCHIDEE-crop predict phenology development
554 based on variations in temperature. The physiological impacts of non-temperature drivers
555 should be further explored in future studies. Finally, observational error may also play an
556 important role in the attribution to OM, which have largely been neglected both in our
557 modelling study and previous statistical attribution (e.g. Zhang *et al.*, 2013). Since the
558 observation over all the stations followed the same protocol (CMA, 1993), it is often assumed
559 that the observational error is uniform across sites and years. Thus, it would not impact the
560 trend estimates and therefore attribution of the LGP trends. Although the assumption is
561 reasonable, the reliability of this assumption remains uncertain. For better data-model
562 integration, we recommend future data collection efforts to further report the error term
563 together with the observations, which will help minimize potential biases in model
564 parameterization and attribution efforts.

565

566 **Conclusions**

567 In this study, we calibrated ORCHIDEE-crop model to represent spatio-temporal
568 variations of rice LGP for three different types of rice in China, and applied this model forced

569 by historical change in climate and transplanting date to attribute the trend in rice LGP. On
570 one hand, we showed that, technically, 1) using Bayes-based particle filter, a generic
571 process-based crop model can be objectively parameterized to represent spatio-temporal
572 variations in rice LGP over China and 2) attribution of LGP trend based on calibrated model
573 provides an alternative to statistical attribution previously used. On the other hand, through
574 factorial simulations, we found that LGP change for different rice types show contrasting
575 dominant drivers. Managements outweighs climate change in affecting LGP of early and
576 single rice, but not for late rice. This suggests that future modelling efforts at global and
577 regional scale should consider various types of rice grown and time-varying management
578 practices. Since large uncertainties still remain in understanding change in LGP, improving
579 documentation of management practices in addition to transplanting date, better description of
580 observational error and ensemble crop modelling can further reduce uncertainties in
581 attributing climate change impacts in future studies.

582

583 **Appendix: Particle filter with sequential importance resampling**

584 The basic idea of the particle filter is to represent the probability distribution function
585 (PDF) of the parameters through an ensemble of parameters, each set of which is called a
586 particle. At each step of the particle filter, the relative importance of the particle, or weight (w)
587 is given by Eq. A1:

$$w_i = \frac{p(y|x_i)}{\sum_{j=1}^N p(y|x_j)} \quad (Eq. A1)$$

588 where N is the number of particles, y is the observation and $p(y|x_i)$ is probability density of the
589 observations given the simulation with the particle x_i ($M(x_i)$) following Eq. A2:

$$p(y|x) = e^{-\frac{(y-M(x))^2}{2\delta^2}} \quad (\text{Eq. A2})$$

590 where δ is the observation error. In this study, we assume observational error is uniform
 591 across sites and years, since the observations over the network were made by trained staff
 592 following the same protocol (CMA, 1993), which are designed to unify and minimize the
 593 observational error across the network. Theoretically, it is possible to analytically have the
 594 PDF of the particles by putting all observations into the equation in one time. However, in
 595 practice, over a large number of sites/time steps, it requires a large number of particles to well
 596 sample the entire parameter space and computationally inefficient by wasting time in barely
 597 possible particles. Therefore, the Markov process (filter) to realize recursive Bayesian
 598 theorem is applied here (Eq. A3):

$$p(x^{1:N}) = p(x^N|x^{N-1}) p(x^{N-1}|x^{N-2}) \dots p(x^2|x^1) \quad (\text{Eq. A3})$$

599 where $x^{1:N}$ is the particle after N iterations. This Markov process makes the entire calculation
 600 iterative. When there is no observation in site i , the Markov process can still evolve by adding
 601 a random term to the particle in site $i-1$, but what we aim is to obtain final posterior PDF of
 602 the parameters given the observations over N sites ($y^{1:N}$):

$$p(x^{1:N}|y^{1:N}) = \frac{p(y^{1:N}|x^{1:N})p(x^{1:N})}{p(y^{1:N})} \quad (\text{Eq. A4})$$

603 Using Eq. A3 to further break down Eq. A4, we obtain Eq. A5:

$$p(x^{1:N}|y^{1:N}) = \frac{p(y^N|x^N)p(x^N)}{p(y^N)} \frac{p(y^{N-1}|x^{N-1})p(x^{N-1})}{p(y^{N-1})} \dots \frac{p(y^1|x^1)p(x^1)}{p(y^1)} \quad (\text{Eq. A5})$$

604 Applying Eq. A2 to Eq. A5, we obtained the numerical solution for all terms from 1 to N . For
 605 each step i , importance resampling is taking place to randomly redraw a new ensemble of
 606 particles from the weighted old ensemble to represent $p(x^i)$, which leads to disregard particles
 607 that have very small weights and thus refine the ensemble. Sometimes the importance

608 resampling may disregard some locally low probably particles but having global significance.
609 Therefore, we usually perform twice of the entire PFSIR process with different re-order
610 observations to test its convergence in order to minimize the potential error due to this. More
611 details and illustration of the particle filter can be found in van Leeuwen (2010). To adapt
612 ORCHIDEE-crop model to different cropping systems, single rice and double rice (early rice
613 and late rice) in China, we adapted particle filter with sequential importance resampling (van
614 Leeuwen, 2009) separately for the three rice types (Table 1).

615

616 Prior parameters of the ORCHIDEE-crop was obtained from (Irfan, 2013). The range of
617 prior parameters were obtained from Sanchez et al. (2014), which synthesized experiment
618 knowledge on the range of basal, optimal and maximum temperature thresholds of rice
619 development, and Valade et al. (2014), which contains modeller's prior knowledge for the
620 range of the parameters. Since we knew little about the prior probability distribution of the
621 parameters, we assumed the prior parameter equally distributed within its range in order to
622 guarantee a well sampling of the entire parameter space. Another issue may limit the
623 capability of PFSIR is the error in the observation data. Unfortunately, accuracy description of
624 the phenology observations are not available except that observations were made following
625 the same standard protocol. However, the dataset is being treated as reliable data source
626 without the need to do further filtering (e.g. Tao et al., 2013; Zhang et al., 2013).

627

628

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636

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785 **Supplementary Information Captions**

786 Supplementary information can be found, in the online version of this article.

787 **Fig. S1.** *Response of phenology development to temperature based on the prior parameters.*

788 **Fig. S2.** *Comparison of trend estimates by parametric tests (linear regression slope) and*
789 *non-parametric tests (Sen's slope).*

790 **Fig. S3.** *Spatial distribution of long-term (>15 years) rice phenology observation sites.*

791 **Fig. S4.** *Spatial relationship between observed length of rice growing period length (LGP)*
792 *and simulated LGP.*

793 **Fig. S5.** *Inter-annual relationship between observed length of rice growing period (LGP) and*
794 *simulated LGP.*

795 **Fig. S6.** *Histogram of change in length of rice growing period (LGP) estimated by*
796 *ORCHIDEE-crop model.*

797 **Fig. S7.** *Spatial distribution of change in length of rice growth period (LGP) over the past*
798 *two decades from observations and factorial simulations.*

799 **Fig. S8.** *Spatial pattern of change in transplanting date over the past two decades.*

800 **Fig. S9.** *Relationship between trend in growing season temperature and trend in LGP residual*
801 *(the difference between observed LGP and simulated LGP after optimization).*

802 **Fig. S10.** *Spatial pattern of change in growing season temperature over the past two decades.*

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