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1 **Identifying trends and associated uncertainties in potential rice production under climate**  
2 **change in Mediterranean areas**

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17

## 18 **Abstract**

19 The future of global rice productions in top producing countries is undermined by the impact of  
20 climate change threatening food security in the near future. In those European Mediterranean areas  
21 where rice is cultivated, this peculiar cropping system plays a crucial role in terms of sociocultural  
22 and ecological issues, and the climate change impact is still scarcely investigated. In this study, we  
23 explored the future trends of potential rice yields in the region considering the multiple sources of  
24 uncertainty associated with climate and yield predictions. Two rice crop models (STICS and  
25 WARM) were calibrated using 20 field experiments carried out in two main European rice  
26 producing areas – i.e., the Italian Lomellina and the French Camargue. These models were then  
27 applied under a range of climate change scenarios in 2030 and 2070 time frames, considering  
28 projections from the combination of four General Circulation Models and two extreme  
29 Representative CO<sub>2</sub> Concentration Pathways (RCP 2.6 and 8.5). We compared the simulated yield  
30 levels with no adaptation, and designed adaptation strategies based on the anticipation of sowing  
31 date and the adoption of varieties with longer crop cycle. Our results showed that with no  
32 adaptation yields would decrease on average by 8% in 2030 and 12% in 2070 in Camargue and  
33 Lomellina, respectively. Future simulated yields in the two areas were lower than in the baseline in  
34 67% (Camargue) and 84% (Lomellina) of the cases. The implementation of both adaptation  
35 strategies proved to be effective in reversing the situation, leading to an average yield increase of  
36 28% and 25% in 2030 and 2070, respectively. The associated probability of lower yields than in  
37 current conditions was 24% in the two sites. Despite the uncertainty in predictions, mainly related  
38 to site, GCM and RCP, our findings indicate that the European rice sector has the potential to  
39 enhance current production levels in a changing climate, if longer cycle varieties will be grown in  
40 Mediterranean rice areas.

## 41 **Keywords**

42 Adaptation strategies, Camargue, Lomellina, rice yields, STICS, WARM

## 43 **Introduction**

44 The effects of climate change on the future rice (*Oryza sativa* L.) production is still under debate in  
45 the three top producing countries – China (Tao and Zhang, 2013), India (Aggarwal and Mall, 2002)  
46 and Indonesia (Naylor et al., 2007) – due to the counterbalance between the beneficial effect of  
47 rising atmospheric CO<sub>2</sub> concentration and the exacerbation of abiotic stresses on crop growth, such  
48 as heat (Baker et al., 1992), drought (Wassmann et al., 2009) and salinity (Redman et al., 2011).  
49 The available estimates are discordant, and range between an increase of 10-15% in 2020 (Tao and  
50 Zhang, 2013) to 7-10% yield losses per every 1 °C increase in air temperature (Peng et al., 2004;  
51 Krishnan et al., 2007). Given the leading role of rice as a staple food for humans (Fitzgerald et al.,  
52 2008; Soora et al., 2013) and the need of doubling crop production by 2050 to meet the projected  
53 demand of the global population (Ray et al., 2013), this research question is in the spotlight, and  
54 efforts are still needed to deepen current knowledge. In the meanwhile, rice growers and  
55 stakeholders of the rice sector are already implementing adaptation strategies, ranging from  
56 individual autonomous local reactions (Dharmarathna et al., 2014) to planned policy interventions  
57 (Huang et al., 2015), in order to alleviate the negative impacts of climate change in the main  
58 producing environments (Howden et al., 2007).

59 Nevertheless, less research has been devoted to analyse the consequences of climate change on rice  
60 production in Europe (EU), where rice is the 6<sup>th</sup> most produced cereal, with almost 4 million tons on  
61 about 650,000 ha in 2013, for an average yield of 6 t ha<sup>-1</sup> (FAOSTAT, 2014). Although not being a  
62 staple food crop in EU, rice plays a pivotal sociocultural (Picazo-Tadeo et al., 2009) and ecological  
63 (Longoni, 2012) role in several Mediterranean countries, where the human consumption is steadily  
64 increasing (Ferrero and Tinarelli, 2007; Worldatlas, 2016). Italy, Spain, Greece, Portugal and  
65 France are the five top European producing countries, and present a higher per capita annual rice  
66 consumption (6-18 kg year<sup>-1</sup>) than in non-producing northern countries (3.5-5.5 kg year<sup>-1</sup>, Maclean  
67 et al., 2002). The typical European rice production system presents paddy cultivation under  
68 continuous flooding during most part of the crop cycle (Hill et al., 1991), and water drainages to

69 allow rooting, top-dressing fertilization, herbicide spraying and harvesting (Fusi et al., 2014). Cold  
70 temperatures are the main environmental constraint to rice production in Mediterranean countries  
71 (Jena and Hardy, 2012). Damages to rice crop due to low temperatures can occur at any growth  
72 stage, being particularly severe at sowing, when they can undermine the germination capacity and  
73 the establishment of rice plants (Ferrero and Tabacchi, 2002), and during microsporogenesis stage  
74 (Dingkuhn et al., 1995), when high diurnal temperature ranges can increase the risk of pollen  
75 sterility (Russo and Callegarin, 1997). With increased temperatures due to climate change, heat  
76 stress could be more frequent on temperate rice crop. Recent findings in rice physiology indicate  
77 that heat stress causing sterility in the exerted part of the panicle is likely to occur even in  
78 Mediterranean countries, especially in warm and humid years (Julia and Dingkuhn, 2013).

79 The complex effects of global warming and CO<sub>2</sub> increase on rice growth in Mediterranean countries  
80 comprise both detrimental and beneficial effects. The meta-analysis carried out by Wang et al.  
81 (2015) reports a percentage yield increase of 24.5% at 660-699 ppm, which is mainly associated to  
82 an increase in the number of panicles and grains per plant. Likewise, available free air CO<sub>2</sub>  
83 enrichment experiments allowed to quantify the atmospheric fertilization benefits on temperate rice  
84 yields in the range 7-15% at 586-645  $\mu\text{mol mol}^{-1}$  for *japonica* type varieties (Kim et al., 2003),  
85 which are the most widespread in EU (Confalonieri and Bocchi, 2005). The increase in air  
86 temperature can lead to the decreased occurrence of cold sterility events, which currently are a  
87 major constraint to European rice yield. Potential positive effects of higher temperature are also  
88 related to the anticipation and the extension of the growing season length (Peng et al., 1995), which  
89 can favour the cultivation of longer cycle varieties, and to the improvement of plant photosynthetic  
90 rates. The latter will probably increase because of the thermal requirements of this tropical crop  
91 (Borjigidai et al., 2006) and due to the higher CO<sub>2</sub> concentration in the atmosphere. The  
92 temperature increase can also cause detrimental effects on future rice production, such as the  
93 shortening of the crop cycle, especially of the grain filling period (Matthews and Wassmann, 2003)  
94 and the increased risk of heat sterility during pollination (Hirabayashi et al., 2015), and the loss of

95 sink activity of the panicle (Kim et al., 2011). As for other driving variables of the biophysical  
96 system (Dieleman et al., 2012), the predominance of the complex interactions on the simple  
97 additive effects between temperature and CO<sub>2</sub> in affecting crop production, constitutes an additional  
98 source of variability in the future trends of rice yield (Long et al., 2006).

99 The complex array of uncertainties connected with the study of the impact of climate change on  
100 crop yield – including observed climate inputs, future CO<sub>2</sub> concentrations, climate model outputs  
101 and projected impacts (Challinor et al., 2009) – makes current projections inherently highly  
102 uncertain (Godfray et al., 2010; Asseng et al., 2013). An effective and standard methodological  
103 framework to quantify these multiple sources of uncertainty is still lacking (Burke et al., 2015),  
104 even if this became a topic by itself (Wesselink et al., 2015). Moreover, the ranking of their  
105 importance is considered a required milestone to improve the understanding of the real impacts of  
106 climate change, and to enhance the credibility of climate change studies for policy makers (Ruiz-  
107 Ramos and Minquez, 2010).

108 To date, the impacts of climate change on rice yield are scarcely investigated in European  
109 production areas, where the impacts of temperature changes in the 21<sup>st</sup> century are expected to be  
110 huge in response to even slight changes in large-scale climatic factors (Gao and Giorgi, 2008), and  
111 to substantially vary at fine spatial scale (Gao et al., 2006). In most studies, the EU rice  
112 Mediterranean region is included in global scale simulations, but its results are never specifically  
113 discussed. For instance, Ray et al. (2014) studied the relations between climate and yield  
114 variabilities in 1979-2008, showing that climate variability is responsible for 13-43% of rice yield  
115 variability in Mediterranean countries, with the average very close to the world one (0.29 and 0.31,  
116 respectively; data retrieved from Supplementary Material). A recent assessment of future rice yields  
117 as affected by climate change was performed in Italy using a single crop model (Bocchiola, 2015).  
118 Focusing on irrigation water use, it reports a general yield increase until mid-century and a decrease  
119 later on. Mediterranean regions are indeed considered as one of the most prominent climate change

120 hotspots (Giorgi, 2006), because they lay in the transition zone between the arid northern African  
 121 climate and the wet-temperate climate of central EU (Mariotti et al., 2015).  
 122 This paper aims at exploring the main trends of future Mediterranean rice yields, and to quantify  
 123 and rank the multiple sources of uncertainty related to climate and yield predictions. Two rice crop  
 124 models were applied in two main European rice producing areas - the Italian Lomellina and the  
 125 French Camargue - to simulate potential rice growth and development in current conditions and  
 126 under a wide range of climate change scenarios, considering projections of four General Circulation  
 127 Models (GCM) and two contrasting Representative CO<sub>2</sub> Concentration pathways (RCP; IPCC,  
 128 2014).

129

## 130 1. Materials and methods

	<u>Activity</u>	<u>Inputs</u>		<u>Model</u>		
		<u>Climate</u>	<u>Other</u>	<u>Climate</u>	<u>Crop</u>	<u>Stat.</u>
<i>Step A</i>	Generation of future weather scenarios	Observed 1991-2010 GCM x RCP	-	X		
<i>Step B</i>	Calibration of the crop models	Observed (7 years)	Field experiment data		X	
<i>Step C</i>	Development of adaptation strategies	Baseline and future scenarios	Calibrated model parameters		X	
<i>Step D</i>	Simulation of baseline and future potential yields	Baseline and future scenarios	Adaptation strategies		X	
<i>Step E</i>	Analysis of variance of simulated future yields	-	Simulated future yields			X

131

132 Figure 1. Activities performed in this study, with associated synthetic input information.

133

134

135 The workflow of the activities performed in this study is presented in Figure 1. *Step A* led to the  
 136 generation of the future weather scenarios (section 2.2) as input for the crop model simulations,  
 137 starting from baseline weather data and using RCP-based GCM projections as input for a weather  
 138 generator. In *Step B*, current weather data were used as input for the crop models, which were  
 139 calibrated against measurements from field experiments performed in the two study areas (section

140 2.3.2). *Step C* aimed at developing the adaptation strategies, which were implemented for crop  
141 model simulations (section 2.3.3). Input data were the baseline and future weather scenarios to  
142 derive (1) the relationships between farmers' sowing dates and air temperature, and (2) new crop  
143 model parameters, which were modified to reproduce alternative varieties to be tested in the future  
144 scenarios. *Step D* concerned the simulation of potential rice yields (section 2.3.3) in current and  
145 future weather scenarios, considering no adaptation, and the implementation of adaptation  
146 strategies. In *Step E*, an analysis of variance was performed to quantify the contribution of each  
147 source of uncertainty to yield variability (section 2.4).

148

## 149 **2.1 Characterization of the study areas**

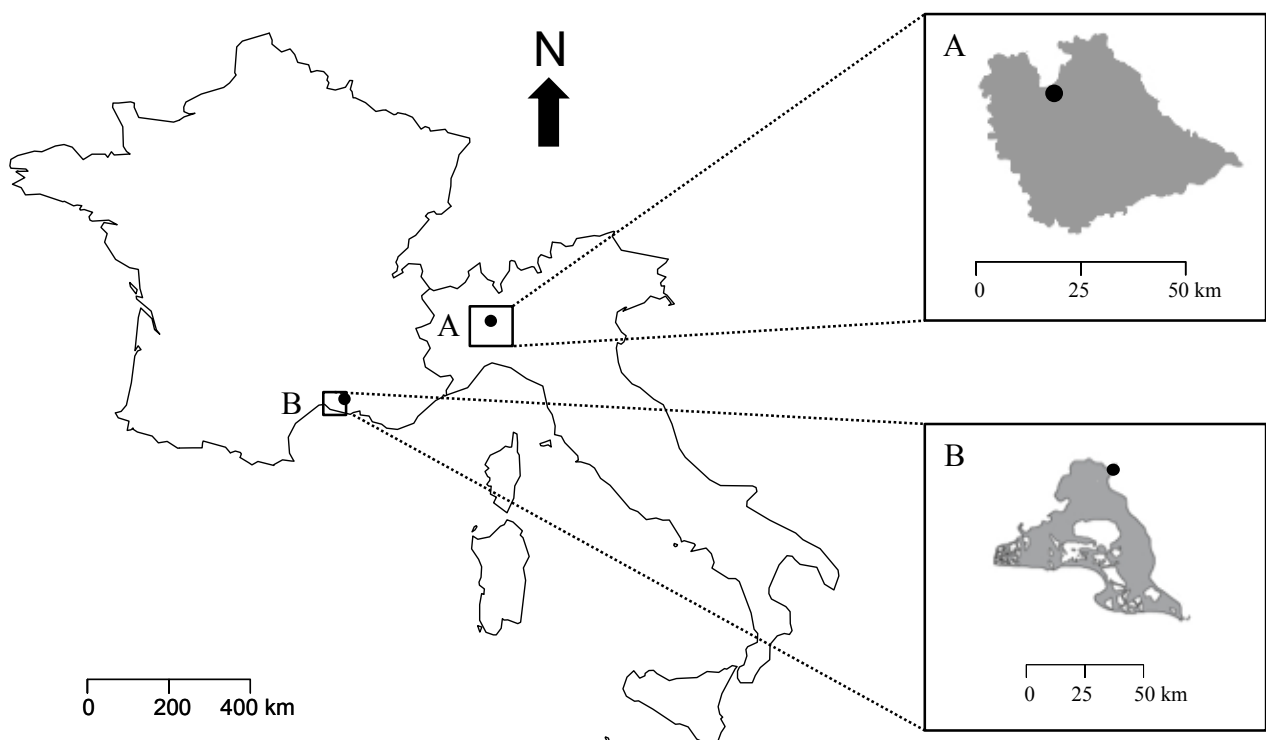
150 The Italian Lomellina and the French Camargue were selected as two representative areas to  
151 evaluate the impact of climate change on European rice production (Figure 2). Rice crop was grown  
152 in 2015 on around 80,000 ha in Lomellina and on around 20,000 ha in Camargue, representing  
153 together 22% of the total EU rice harvested area (Ente Nazionale Risi, [www.enterisi.it](http://www.enterisi.it); FAOSTAT,  
154 2014).

155 According to the updated Köppen-Geiger climate classification (Peel et al., 2007) and to the  
156 environmental stratification of EU (Metzger et al., 2005), both areas fall into the  
157 temperate/mesothermal climatic group, with Lomellina belonging to the North Mediterranean and  
158 Camargue to the South Mediterranean environmental zone. The French and Italian rice areas  
159 present hot summers and mild to cool winters, with differences in their rainfall patterns.  
160 Precipitations are mainly distributed during autumn and winter months, being on average higher in  
161 Lomellina (938 mm) than in Camargue (745 mm). Average air temperatures during the rice  
162 growing season (from May to September) range from 19.9°C in Camargue to 20.5°C in Lomellina  
163 in the period 1991-2010.

164 The typical agricultural management of rice fields presents direct seeding and continuous flooding  
165 until milky ripening stage, with two-three water drainages during the growing season to promote



166 rooting and before the application of weed control products and top dress fertilizers (mainly urea,  
167 average dose  $150 \text{ kg ha}^{-1}$ ), which are usually split at sowing, tillering and panicle differentiation  
168 stage. The most widespread rice varieties mainly belong to the *japonica* ecotype, with main  
169 differences in the duration of the growing cycle.  
170 Weed infestation and cold temperatures are among the main constraints to rice production during  
171 the crop establishment phase in both French and Italian rice areas, whereas spikelet sterility due to  
172 cold air irruptions around flowering (Biologische Bundesanstalt, Bundessortenamt und Chemische  
173 Industrie, BBCH codes 61-69) often occurs leading to yield losses (Mariani et al., 2009).



174  
175 Figure 2. Location of the two study areas (A : Lomellina, B : Camargue). Black dots represent the  
176 locations of the meteorological stations  
177

## 178 2.2 Current and future weather scenarios

179 For current weather scenarios, 20-years series of daily weather data for the period 1991-2010 were  
180 collected from weather stations located inside the French and Italian rice areas. Castello d'Agogna  
181 ( $45^{\circ}14' \text{ N}$ ,  $08^{\circ}41' \text{ E}$ ) and Fourques ( $42^{\circ}58' \text{ N}$ ,  $2^{\circ}78' \text{ E}$ ) were selected for the Lomellina and  
182 Camargue case studies, respectively (Figure 2). The available weather variables were daily  
183 maximum and minimum air temperature ( $^{\circ}\text{C}$ ), precipitation ( $\text{mm d}^{-1}$ ), global solar radiation ( $\text{MJ m}^{-2}$ )

184  $d^{-1}$ ), average wind speed ( $m s^{-1}$ ) and evapotranspiration ( $mm d^{-1}$ ). These baseline data and four  
185 GCM realizations of two contrasting RCP were used to generate the 20-years future weather series  
186 to consider a range of plausible impacts of the changes in atmospheric composition due to the  
187 effects of technology, economy, lifestyle, and policy development on climate (IPCC, 2014). Two  
188 future time frames were considered, referring to the near (2030) and long-term (2070) futures.  
189 The GCM were randomly selected among the ones included in the Coupled Model Intercomparison  
190 Project (CMIP5, <http://cmip-pcmdi.llnl.gov/cmip5/>): the Norwegian Earth System Model  
191 (NOResm, Tjiputra et al., 2013), the Model for Interdisciplinary Research on Climate (MIROC-  
192 ESM, Watanabe et al., 2011), the Hadley Centre Global Environmental Model version 2  
193 (HadGEM2-ES, Collins et al., 2011), and the GCM developed by the Goddard Institute for Space  
194 Studies (GISS-ES, Schmidt et al., 2006).

195 The two extremes of the RCP of greenhouse gas (GHG) concentration proposed by IPCC were used  
196 in this study: the RCP 2.6, which assumes a peak of global annual GHG emissions between 2010-  
197 2020 and a radiative increase up to  $2.6 W m^{-2}$ , with  $CO_2$  concentration reaching 420 ppm in 2100,  
198 and the RCP 8.5, projecting a continuous rise of GHG emissions throughout the 21<sup>st</sup> century with a  
199 radiative increase of  $8.5 W m^{-2}$ , with  $CO_2$  concentration reaching 936 ppm in 2100 (IPCC, 2014).

200 The  $CO_2$  concentration for baseline conditions was set to 382 ppm, and the future  $CO_2$   
201 concentrations used as input in the simulation experiment were 438 ppm (2030) and 444 ppm  
202 (2070) for RCP 2.6, and 438 ppm (2030) and 660 ppm (2070) for RCP 8.5 (IPCC, 2013).

203 The average monthly absolute anomalies of temperature and precipitation in the period 2021-2040  
204 for 2030 time frame, and 2061-2080 for 2070 time frame (difference or ratio between the future and  
205 the present value of the variable; Déqué et al., 2007), corresponding to each GCM  $\times$  RCP  
206 combination, were downloaded from the Program for Climate Model Diagnosis and  
207 Intercomparison data portal (<https://pcmdi.llnl.gov/search/cmip5/>). They were then used to  
208 modulate the parameters of the CLIMAK weather generator (Danuso, 2002), in order to generate  
209 the 20-years of future weather series to be used in the simulation experiment, following the

210 procedure used by Confalonieri et al. (2013), Cappelli et al. (2015) and Paleari et al. (2015). In this  
211 simulation experiment 34 weather series of 20-years were used, as the sum of the 2 baseline for  
212 Lomellina and Camargue and of 32 future weather scenarios, as the product of 2 RCP  $\times$  4 GCM  $\times$  2  
213 future time frames  $\times$  2 study areas.

214

## 215 **2.3. Simulation experiment design**

### 216 **2.3.1. Crop simulation models**

217 The simulation of rice growth and development in baseline and future weather scenarios was  
218 performed at potential production level, i.e., defined by the genotype of the rice variety and by solar  
219 radiation, temperature and CO<sub>2</sub> concentration (De Wit and Penning de Vries, 1982; Rabbinge,  
220 1993). We did not consider the limiting effects of water and nutrient availability on yield – the  
221 attainable production level – because rice-cropping systems are flooded and receive generally a  
222 high fertilization rate in both areas. We used the generic crop model STICS (Brisson et al., 1998)  
223 adapted for rice (Ruget et al., 2016) and the rice model WARM (Confalonieri et al., 2009) to  
224 perform the simulation experiment, as these two models were developed under temperate  
225 conditions. Although they both simulate crop phenological development as a function of thermal  
226 time accumulation and share the main concept of radiation use efficiency (RUE, g MJ<sup>-1</sup>, Warren  
227 Wilson, 1967) to reproduce biomass growth, they markedly differ in the formalization of the  
228 algorithms used to mimic crop growth and respond to weather input data (Table 1). Main  
229 differences between the two models are the time step to compute rice growth and development –  
230 hourly for WARM and daily for STICS – and the formalization of the plant processes leading to the  
231 dynamic increase of leaf area index and to the partitioning of assimilates to leaves, stems and  
232 panicles. Hourly data of air temperature and global radiation as input for the WARM model were  
233 estimated according to Campbell (1985) and Chen et al. (1999) starting from daily data.  
234 The WARM model daily updates the leaf area index (m<sup>2</sup> m<sup>-2</sup>) by multiplying the daily increase of  
235 leaves biomass (kg m<sup>-2</sup>) by the specific leaf area (m<sup>2</sup> kg<sup>-1</sup>), and computes leaves senescence as

236 driven by a threshold of thermal time, whereas STICS calculates the leaf area index increase as  
 237 mediated by air temperature. The partitioning pattern in STICS is driven by a dynamic harvest  
 238 index, which is upper limited by the product of grain numbers by maximum grain weight, whereas  
 239 in WARM it depends solely on crop development stage, with the weight of reproductive organs  
 240 starting to grow after panicle initiation stage. The maximum value of radiation use efficiency is  
 241 modulated in both models by temperature, radiation, development stage and CO<sub>2</sub> concentration,  
 242 according to different modelling approaches. The two models differ in the simulation of the impacts  
 243 of cold and heat stress on rice yield. The WARM model simulates a reduction of spikelet fertility  
 244 due to cold and heat stresses acting in a critical time window around flowering, whereas STICS  
 245 stops the grain filling process in post-anthesis while decreasing the number of grains during the  
 246 ripening period as a response to low and high temperatures. The beneficial effect of increasing  
 247 atmospheric CO<sub>2</sub> in future climate scenarios is simulated by the two models with empirical  
 248 functions (Appendix B).

249

250 Table 1. Modelling approaches used by the WARM and STICS models to simulate plant processes,  
 251 as employed in this study.

<b>Process</b>	<b>Sub process</b>	<b>WARM</b>	<b>STICS</b>
Phenology	Emergence	Thermal time sum	Sowing depth and soil humidity
	Flowering and maturity dates	Thermal time sum	Thermal time sum
	Thermal time accumulation	Nonlinear function between minimum, optimum and maximum temperature	Trapezoidal linear function between minimum, two optimum and maximum temperature
	Input temperature	Air temperature	Crop temperature
	Time step	Hourly	Daily
Leaf area dynamics	Leaf area index increase	Driven by specific leaf area and leaves biomass	Driven by temperature
	Leaf senescence	Thermal time, leaf life duration	Thermal time, leaf life duration
Biomass accumulation	Photosynthesis	Net photosynthesis, a single value of maximum radiation use efficiency	Net photosynthesis, three values of maximum radiation use efficiency according to the phenological phase.

	Time step	Hourly	Daily
Limiting factors on radiation use efficiency	Temperature	Nonlinear function between minimum, optimum and maximum temperature	Linear function between minimum, optimum and maximum temperature
	Radiation	Linear decrease above a radiation threshold	Nonlinear decrease of the daily relation between biomass increase and intercepted radiation
	Development stage	Linear decrease after flowering	Variation of the value of maximum radiation use efficiency according to the phenological phase
	CO <sub>2</sub> effect	Exponential function, Eq. 2	Exponential function, Eq. 1
Partitioning of assimilates	Vegetative organs	Nonlinear, driven by development stage	Fixed parameter of the ratio between daily growth of leaves and stems
	Reproductive organs	Driven by development stage, starting from panicle initiation	Dynamic harvest index and maximum grain number fixed at flowering, maximum grain weight as genotypic parameter
Limiting factors to yield accumulation	Extreme temperatures	Around flowering	During ripening period
	Damage	Heat/cold sterility acting on panicle biomass	Stop of grain filling, reduction of grain numbers during early ripening

252

### 253 2.3.2. Models' calibration in current weather conditions

254 We calibrated the two crop models using phenological observations (dates of flowering and  
255 maturity) and dynamic field data of leaf area index (LAI, m<sup>2</sup> m<sup>-2</sup>) and aboveground biomass (AGB,  
256 t ha<sup>-1</sup>) collected in 10 experimental trials in Lomellina (years 1989, 1990, 1995, 1996) and in  
257 surveys in 10 farmer fields in Camargue (years 1987, 1988 and 2009). Full information on these  
258 datasets including the description of the site, the sowing date, the variety and synthetic data on crop  
259 development and growth are provided in Appendix A. The agronomic management of the fields  
260 aimed at growing rice crop at potential production level. Experiments were carried out under flood  
261 irrigation and non-limiting nitrogen conditions, in order to avoid water and nitrogen stresses during  
262 the whole crop cycle. Weeds were controlled in pre-sowing and post-emergence in both sites, and a  
263 chemical treatment against blast disease was applied around flowering in Lomellina experiments.

264 The field datasets refer only to *japonica*-type varieties, which were split in two groups according to  
265 the length of their crop cycle (*japonica* early and *japonica* medium).

266 AGB and LAI were measured several times during the crop cycle to characterize the crop growth  
267 dynamics, whereas yield was sampled at harvest. The AGB samples were oven-dried until constant  
268 weight, whereas LAI was sampled by destructive planimetric methods, according to Jonckheere et  
269 al. (2004). The BBCH scale (Lancashire et al., 1991) was used to assess the main rice phenological  
270 stages: emergence (BBCH=10), flowering (BBCH=65) and physiological maturity (BBCH=89).

271 STICS and WARM were calibrated and evaluated separately for *japonica* early and medium  
272 varieties. For each group, 10 French and 10 Italian datasets were split into independent calibration  
273 and evaluation subsets to assure the applicability of the two models across study areas. The crop  
274 model calibration was performed independently for the two models via automatic optimization tools  
275 using the root mean square error between simulated data and measurements as the objective  
276 function, and tuning parameter values within their biophysical ranges. For both models, we started  
277 from default parameterization for rice crop. For WARM model, the parameters under calibration  
278 involved with phenological development were the thermal thresholds to reach flowering and  
279 maturity ( $^{\circ}\text{C day}$ ), whereas to reproduce organs growth the potential radiation use efficiency ( $\text{g MJ}^{-1}$ ),  
280 the three cardinal temperatures for biomass accumulation (minimum, optimum, maximum  
281 temperature,  $^{\circ}\text{C}$ ), the partitioning of assimilated to leaves at emergence (0-1, dimensionless), and  
282 the specific leaf area at emergence and tillering ( $\text{m}^2 \text{kg}^{-1}$ ). In STICS, phenology was calibrated by  
283 adjusting the thermal time requirements ( $^{\circ}\text{C day}^{-1}$ ) between (i) emergence and maximum leaf area  
284 increase, (ii) beginning of stem elongation and maximum LAI, (iii) emergence and beginning of  
285 grain filling, (iv) flowering and maturity, and the leaf life duration ( $^{\circ}\text{C day}^{-1}$ ). The calibrated  
286 parameters related to biomass accumulation were the maximum rate of gross leaf surface area  
287 production ( $\text{m}^2 \text{plant degree day}^{-1}$ ), the coefficient of decrease of maximum leaf area as function of  
288 plant density (dimensionless), the potential radiation use efficiency ( $\text{g MJ}^{-1}$ ), the speed of thermal  
289 increase of harvest index ( $\text{g grain g plant}^{-1} \text{day}^{-1}$ ), the maximum grain weight (g) and the maximum

290 number of grains (grains m<sup>-2</sup>). The calibrated temperature response functions to simulate both  
291 phenological development and the limitation to radiation use efficiency are reported in Appendix C,  
292 as well as the model parameters and the results of model calibration and evaluation.

293

### 294 **2.3.3. Simulations in current and future weather scenarios**

295 The calibrated sets of model parameters characterizing current rice varieties were used to simulate  
296 potential rice yield in baseline weather scenario (1991-2010). Simulations were performed by  
297 setting May, 1<sup>st</sup> as a fixed sowing date in the two study areas, according to available datasets,  
298 farmers' interviews and expert knowledge. The simulation of the future trends of rice yield in the  
299 two areas were performed adopting the same model parameters and sowing date than in baseline  
300 scenario, and by testing the implementation of three adaptation strategies: (1) the anticipation of the  
301 sowing date (*sowing* adaptation), (2) the adoption of varieties with a longer crop cycle (*variety*  
302 adaptation), or (3) the combination of *sowing* and *variety* adaptations (*double* adaptation).

303 The *sowing* adaptation corresponds to a shifting of the rice sowing date according to a mathematical  
304 rule, which was derived on baseline weather scenarios. Considering May 1<sup>st</sup> as the average sowing  
305 date in current conditions, we computed the number of times when the weekly moving average of  
306 daily average air temperature was above 10°C (Gao et al., 1983) in the period March, 1<sup>st</sup> - May, 1<sup>st</sup>.

307 The application of this rule led to different values in the two study sites: in Camargue, i.e., 6.3  
308 weekly averages were above 10°C in the specified two-months period, and 4.3 in Lomellina. Then,  
309 we applied the same rule and thresholds on the future 20-year weather series for Camargue and  
310 Lomellina, in order to derive the new sowing dates to be used in future weather scenarios (Table 2).

311 The *variety* adaptation was developed using a 1-year weather series, computed by daily averaging  
312 the 32 future weather scenarios resulting by all the available combinations of 4 GCM × 2 RCP × 2  
313 sites. This choice allowed us to obtain average weather conditions from the GCM and RCP  
314 ensemble projections, leading to calibrate two model parameter sets, i.e., one for *japonica* medium  
315 and the other for *japonica* late variety.

316 The calibrated values of thermal time threshold to reach flowering and maturity dates in STICS and  
 317 WARM were adjusted by running the two models on this synthetic year, using the average sowing  
 318 date coming from *sowing* adaptation, and forcing the length of the crop cycle to match 140 days and  
 319 160 days, as representative of *japonica* medium and late varieties. Compared to calibrated sets of  
 320 parameters, the values changes involved only the thermal thresholds, i.e. amount of the growing  
 321 degree-days required to reach flowering and maturity stage in the two models. The ratio between  
 322 the thermal time requirements in the periods emergence-flowering and flowering-maturity was kept  
 323 equal to the model calibration in current weather conditions.

324

325 Table 2. Simulation settings adopted for the simulation of potential rice production in current and  
 326 future weather conditions, considering the implementation of *sowing* (shift of the sowing date) and  
 327 *variety* (adoption of varieties with longer crop cycle) adaptation strategies. JE = *japonica* early, JM  
 328 = *japonica* medium, JL = *japonica* late

Site	Time horizon	Setting	Adaptation strategy			
			No	<i>Sowing</i>	<i>Variety</i>	<i>Double</i>
Camargue	2030	Sowing	May, 1 <sup>st</sup>	April, 21 <sup>st</sup>	May, 1 <sup>st</sup>	April, 21 <sup>st</sup>
		Variety	JE, JM	JE, JM	JM, JL	JM, JL
	2070	Sowing	May, 1 <sup>st</sup>	April, 9 <sup>th</sup>	May, 1 <sup>st</sup>	April, 9 <sup>th</sup>
		Variety	JE, JM	JE, JM	JM, JL	JM, JL
Lomellina	2030	Sowing	May, 1 <sup>st</sup>	April, 26 <sup>th</sup>	May, 1 <sup>st</sup>	April, 26 <sup>th</sup>
		Variety	JE, JM	JE, JM	JM, JL	JM, JL
	2070	Sowing	May, 1 <sup>st</sup>	April, 20 <sup>th</sup>	May, 1 <sup>st</sup>	April, 20 <sup>th</sup>
		Variety	JE, JM	JE, JM	JM, JL	JM, JL

329

## 330 2.4 Statistical analysis

331 Uncertainties in yield predictions attributable to the GCM, the RCP, and the crop model were  
 332 evaluated with an analysis of variance together with the effects of the time frame, the site and the  
 333 variety group. The contribution of each source of uncertainty was assessed by the Mean Squared  
 334 Error (MS), calculated as the sum of squares divided by the associated number of degrees of  
 335 freedom (df). MS was used to compare the contributions of the different factors to the total  
 336 variability in simulated rice yields (the highest the MS of a factor, the highest its contribution). The

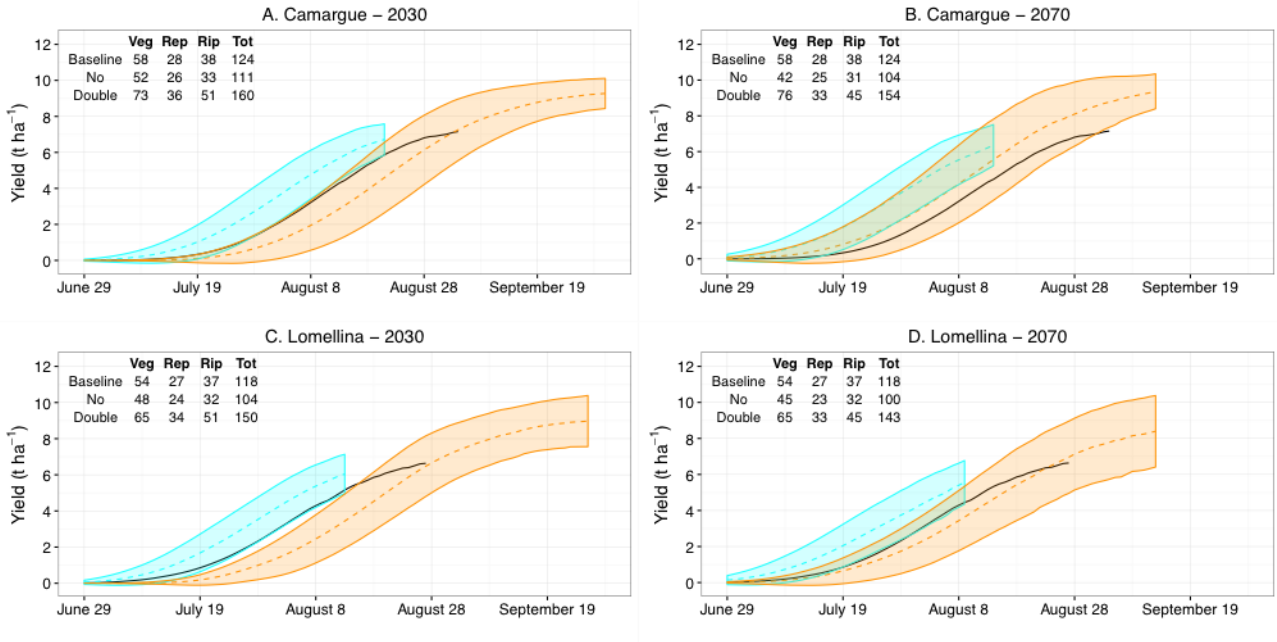


337 significance of each factor was then evaluated using F-tests. Finally, the goodness-of-fit of the  
338 model was assessed by the adjusted  $R^2$  and the size of the errors in the residuals (Root Mean Square  
339 Error, RMSE). All analyses were performed with the R software version 3.2.3 (R Development core  
340 team, 2015). The analysis of variance was performed using the 'aov' function and the RMSE was  
341 calculated using the 'rmse' function of package hydroGOF (Zambrano-Bigiarini, 2014).  
342

343 **3. Results**

344 **3.1. Future trends of rice yield**

345 **3.1.1. Yield dynamics**



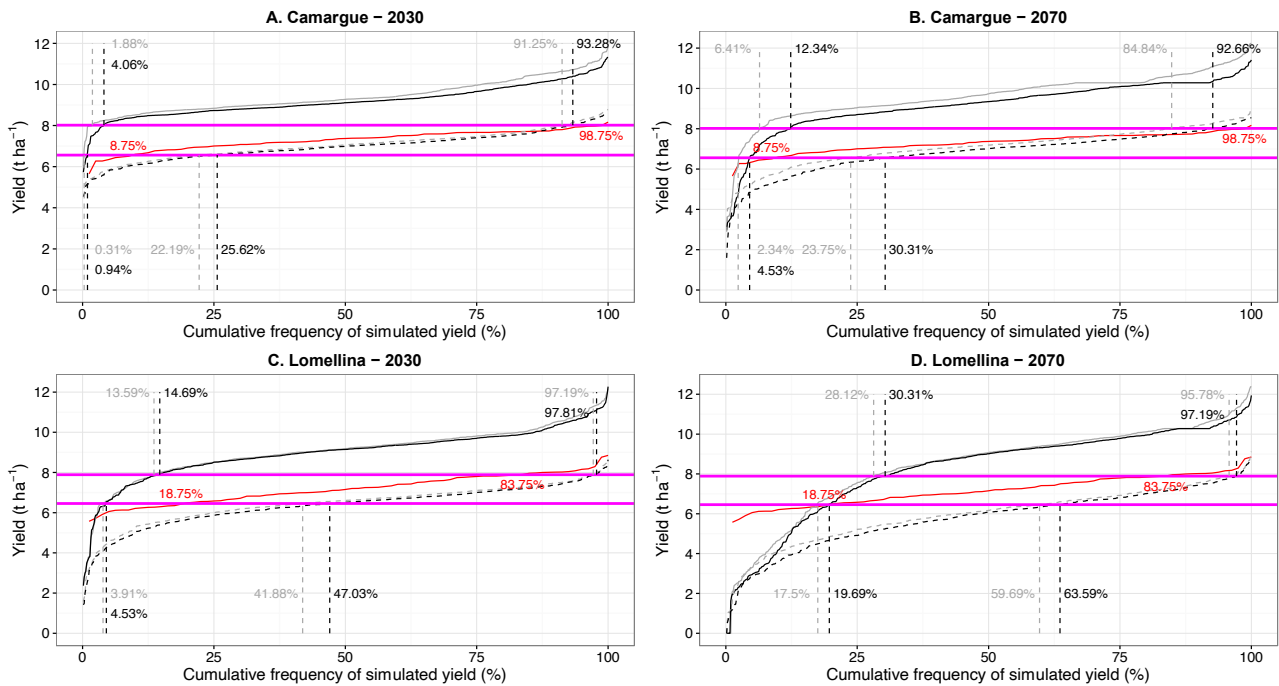
346

347 Figure 3. Dynamic of simulated panicle biomass growth from panicle initiation to physiological  
 348 maturity in baseline (black line) and in future weather scenarios, considering no adaptation (cyan)  
 349 and the implementation of double adaptation (considering together *sowing* and *variety* adaptations,  
 350 orange). Plotted values are the mean of daily data simulated by the two crop models in the baseline  
 351 (solid black line), and in the future (i.e., considering all crop model × variety × GCM × RCP  
 352 combinations for no adaptation – cyan dashed line, varieties *japonica* early and medium – and with  
 353 *sowing* and *variety* adaptation – orange dashed line, varieties *japonica* medium and late) with  
 354 associated standard deviation (extreme coloured lines, for future conditions only). Data are  
 355 presented divided by site (Camargue, A and B; Lomellina, C and D) and time frame (2030, A and  
 356 C; 2070, B and D). For each combination site × time frame, the average duration of rice growth  
 357 stages is reported in number of days (Veg-vegetative period, from germination to panicle initiation;  
 358 Rep-reproductive period, from panicle initiation to flowering; Rip-ripening, from flowering to  
 359 maturity; Tot-total cycle length, from germination to maturity).  
 360

361 The results related to yield dynamics simulated under current/climate change scenarios are  
 362 presented in Figure 3. In 2030, the simulation of rice phenological development in both sites with  
 363 no adaptation (Figure 3A, C) led to a shortening of the crop cycle of 13.5 days due to an  
 364 anticipation of the main rice growth stages (-6 days for vegetative period, -2.5 days for reproductive  
 365 period and -5 days for the ripening period). In 2070, the further anticipation of the main  
 366 phenological phases (-9.5 days for vegetative period, -3.5 days for reproductive period and -6 days

367 for ripening) led to a shortening of the whole crop cycle of 19 days. The combined effect of the  
368 anticipation of sowing dates and the adoption of varieties with higher thermal requirements (*double*  
369 adaptation) determined a longer duration of the main phenological stages and their delayed  
370 occurrence with respect to both no adaptation and baseline simulations (Figure 3B, D). This effect  
371 was clearer in 2030 (+13 days for vegetative period, +7.5 days for reproductive period and +13.5  
372 days for ripening), whereas in 2070 the increase of air temperature smoothed these differences,  
373 especially for reproductive (+5.5 days) and grain filling (+7.5 days) period. Therefore, the average  
374 duration of the whole crop cycle was longer in 2030 (155 days) than in 2070 (148.5 days). On  
375 average, the impact of climate change on the shortening of the crop cycle was similar in the two  
376 case studies, with -32 days in 2030 and -30 days in 2070 in Lomellina and -36 days in 2030 and -25  
377 days in Camargue.

378 With no adaptation, the differences in simulated yield between the two sites were small in 2030, and  
379 the associated mean yields ranged between 6.3 t ha<sup>-1</sup> (Lomellina) and 7 t ha<sup>-1</sup> (Camargue), being  
380 lower than in baseline conditions by -4.5% ÷ -11.8% (average -8.2%) for Camargue and Lomellina,  
381 respectively. In 2070, a decrease of final yield was simulated in Lomellina (5.8 t ha<sup>-1</sup>) whereas in  
382 Camargue mean yield remained more stable (6.8 t ha<sup>-1</sup>), because of the beneficial effect of the  
383 temperature increase on rice growth rates, which counterbalanced the shortening in phenological  
384 development. This led, with respect to baseline simulated yields, to smaller yield loss in Camargue  
385 (-6.4%) than in Lomellina (-19.6%) in 2070. The implementation of *double* adaptation in Camargue  
386 led to mean yield in 2070 (9.6 t ha<sup>-1</sup>) even higher than in 2030 (9.4 t ha<sup>-1</sup>). On the contrary, mean  
387 simulated yield were higher in 2030 (9 t ha<sup>-1</sup>) than in 2070 (8.4 t ha<sup>-1</sup>) in Lomellina. For both time  
388 frames, yield increases, relatively to site specific baseline conditions, were lower in Lomellina than  
389 in Camargue, with a mean increase of +26% in 2030 and +16.9% in 2070 in Lomellina, while  
390 Camargue experienced average yield increases of +29.2% and +31.8% in 2030 and 2070,  
391 respectively.



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Figure 4. Cumulative frequency distribution of simulated yields in site-specific baseline and in future weather scenarios with no adaptation and with the implementation of the three adaptation strategies, as compared to the simulations in baseline conditions for the two sites (Camargue, A and B; Lomellina, C and D) and the two time frames (2030, A and C; 2070, B and D). Red line indicates the site-specific baseline; Dotted black line indicates no adaptation; Dotted grey line indicates Sowing adaptation; Full black line indicates the Variety adaptation; and Full grey line indicates the double adaptation; Magenta lower and upper lines correspond to -10% and +10% of site-specific mean baseline yield, respectively. Numbers correspond to the frequency of simulated yields above or below the  $\pm 10\%$  mean baseline yield, respectively.

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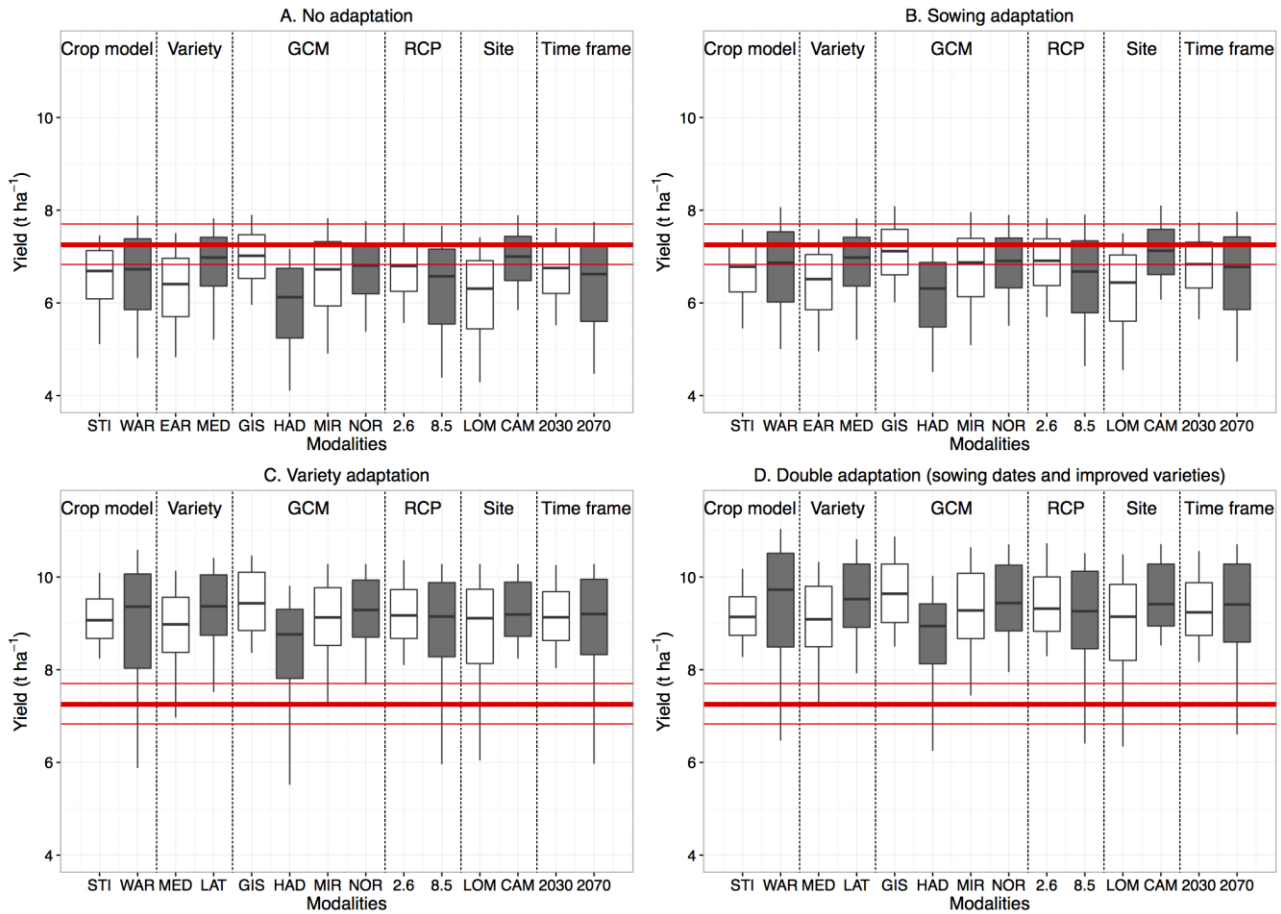
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The cumulative distributions of simulated potential yields in baseline and scenarios in both sites and future time frames are displayed in Figure 4. Simulations with no adaptation led to the lowest yields in all conditions tested. In Camargue, values ranged from 4.5 t ha<sup>-1</sup> to 8.6 t ha<sup>-1</sup> in 2030 and from 1.6 t ha<sup>-1</sup> to 8.5 t ha<sup>-1</sup> in 2070. In Lomellina, simulated yields were even lower, ranging from 1.4 t ha<sup>-1</sup> to 8.6 t ha<sup>-1</sup> in 2030 and from 0 t ha<sup>-1</sup> to 8.8 t ha<sup>-1</sup> in 2070 (see Appendix D for details). The benefits due to the implementation of *double* adaptation were consistent, since it allowed simulated yields ranging between 6 t ha<sup>-1</sup> and 11.8 t ha<sup>-1</sup> in 2030, and between 3 t ha<sup>-1</sup> and 12.2 t ha<sup>-1</sup> in 2070 in Camargue. In Lomellina, simulated yields were in the range 2.5-12.2 t ha<sup>-1</sup> in 2030 and 0-12.4 t ha<sup>-1</sup> in 2070. The almost total yield loss (around 0 t ha<sup>-1</sup>) simulated in 2070 corresponded to the

414 occurrence of massive heat stress due to extreme weather conditions, which were more frequent in  
415 Lomellina than in Camargue in almost all of simulations (90%) for each adaptation strategy (mean  
416 difference of 4 days for *double* adaptation, and of 3 days for no, *sowing* and *variety* adaptation; see  
417 Appendix E). We refer here to “heat stress” as the combined effects of panicle sterility simulated by  
418 WARM and of the reduction of grain number and weight simulated by STICS.

419 In baseline, the frequency of simulated yields leading to yield loss above 10% was lower in  
420 Camargue (8.75%) than in Lomellina (18.75%) (Figure 4). Similarly, a lower number of  
421 simulations resulted in yields gain above 10% in Camargue (1.25%) than in Lomellina (16.25%).  
422 No adaptation and *sowing* adaptation led to much higher risks to get more than 10% of yield loss, as  
423 compared with the site-specific mean of the baseline scenario (more than 22% and 41% of  
424 simulated yields, respectively, see Figure 4). No adaptation and *sowing* adaptation led to more than  
425 10% of yield increase in less than 10% and 5% of the cases in Camargue and Lomellina,  
426 respectively. The number of simulated future yields associated with more than 10% of yield loss  
427 with respect to the site-specific mean baseline was strongly reduced with *variety* and *double*  
428 adaptation (maximum of 5% and 20% in Camargue and Lomellina, respectively). Simulated yields  
429 for *variety* and *double* adaptation resulted in more than 10% of yield increase, as compared to the  
430 site-specific mean baseline, in most of the simulations (more than 87% and 69% of the simulated  
431 yields in Camargue and Lomellina, respectively). The risks of yields with more than 10% of yield  
432 loss were lower in 2030 than in 2070 for both sites, with larger differences between the two time  
433 frames in Lomellina (Figure 4). The fraction of simulated yields with more than 10% of yield  
434 increase was also larger in 2030 than in 2070, with larger differences in Camargue (e.g., 9% and  
435 15% of the simulated yields with *sowing* adaptation in 2030 and 2070, respectively). The effect of  
436 the *sowing* adaptation on final yield was negligible in all conditions tested, as the distributions of  
437 simulations with earlier sowing dates were almost overlapped with the ones with current sowing  
438 date (May, 1<sup>st</sup>), whereas simulations with *double* adaptation were very similar than with *variety*  
439 adaptation.

440  
 441 **3.2 Quantifying yield uncertainty due to climate changes projections**  
 442 **3.2.1. Overview of the magnitude of each factor**



443  
 444 Figure 5. Boxplots of final yields simulated according to each modality (x-axis) of the six factors  
 445 considered here (crop model, group of varieties, GCM, RCP, site and time frame).  
 446 Plotted values refer to simulations with no adaptation (A), according to the implementation of  
 447 *sowing* (B) and *variety* adaptation (C) and to *double* adaptation (D).  
 448 Extreme values correspond to quantiles 10 and 90. STI: Stics; WAR: Warm; EAR: early variety;  
 449 MED: medium variety; LAT: late variety; GIS: Giss; HAD: Hadgem; MIR: Miroc; NOR: Noresm;  
 450 2.6: RCP 2.6; 8.5: RCP 8.5; LOM: Lomellina; CAM: Camargue; 2030: Time frame 2030; 2070:  
 451 Time frame 2070. In red are indicated median baseline yield (bold line), and 25<sup>th</sup> and 75<sup>th</sup>  
 452 quantiles considering together the simulated yields of the two sites, the two varieties and the two crop  
 453 models.  
 454

455 Figure 5 summarizes the effects of each factor by synthetizing its distribution (10, 25, 50, 75 and  
 456 90<sup>th</sup> quantiles) for each factor modality (e.g., STICS and WARM modalities for the crop model  
 457 factor). The ranking of the modalities' median values was stable for every factor whatever the  
 458 adaptation strategy considered, whereas the associated yield variability differed according to the

459 different modalities of each factor (Figure 5). Median yield values and yield variability simulated  
 460 by WARM were higher than for STICS, this difference increasing with *variety* and *double*  
 461 adaptation (Figure 5). The adoption of varieties with a longer cycle had an opposite impact on the  
 462 yield variability simulated by the two models, with WARM increasing and STICS reducing the  
 463 yield variability. The varieties with longer cycles displayed higher yields than early varieties,  
 464 consistently between the four tested strategies. The yield variability associated to GCM was similar  
 465 between the four modalities.

466 Median yields for RCP 2.6 were higher than for RCP 8.5 for the four strategies, with lower  
 467 differences for the *variety* and *double* adaptations. Yields simulated with RCP 2.6 were less variable  
 468 than with RCP 8.5. Lomellina median yields showed a wider distribution, and lower values, than  
 469 Camargue yields for all adaptation strategies. The median yield difference between the two sites  
 470 was lower with *variety* and *double* adaptation, as compared to no and *sowing* adaptation (Figure 5).  
 471 The median simulated yield variability was higher in 2070 than in 2030, while their ranking differed  
 472 between no and *sowing* adaptations compared to *variety* and *double* adaptation. For *variety* and  
 473 *double* adaptation, most of the simulated yields were above the median, and even the first quartile  
 474 of baseline yield distribution (Figure 5). Thus, while the ranking of factors and modalities remained  
 475 stable for the different adaptation strategies, there was a systematic yield increase when adapting  
 476 the variety (*variety* and *double* adaptation), as compared to no adaptation and to *sowing* adaptation.

477

### 478 **3.2.2. Ranking the components of uncertainty**

479 Table 3. Analysis of variance of mean future yields with and without adaptation strategies,  
 480 considering together the two time frames (2030 and 2070), the two RCP (2.6 and 8.5), the four  
 481 GCM (Giss, Hadgem, Miroc and Noresm), the two sites (Camargue and Lomellina), the two crop  
 482 models (Stics and Warm), and the two groups of variety.

Factor	d.f.	No adaptation		<i>Sowing</i>		<i>Variety</i>		<i>Double</i>	
		MS	p-value	MS	p-value	MS	p-value	MS	p-value
Time frame	1	79	<0.001	30	<0.001	97	<0.001	35	<0.001
RCP	1	137	<0.001	109	<0.001	166	<0.001	175	<0.001
GCM	3	136	<0.001	130	<0.001	158	<0.001	157	<0.001
Site	1	455	<0.001	564	<0.001	217	<0.001	410	<0.001

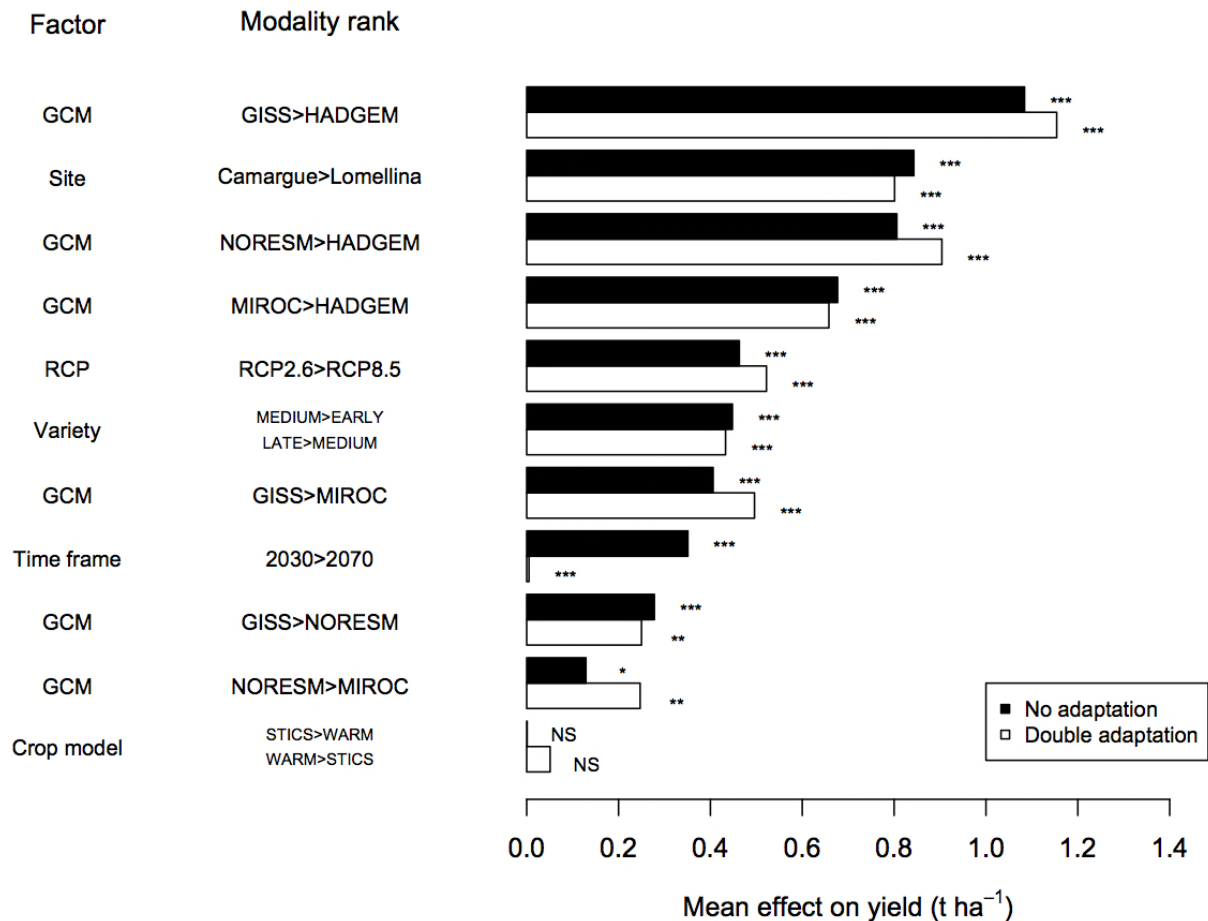
Crop model	1	0	0.981	1	0.252	59	<0.001	2	0.371
Variety group	1	128	<0.001	221	<0.001	114	<0.001	120	<0.001
Adjusted R <sup>2</sup>			0.329		0.339		0.173		0.187
RMSE			0.976		0.921		1.440		1.424

483 d.f. : number of degrees of freedom ; MS : Mean Squared Error ; RMSE : Root Mean Squared Error  
484 (in t ha<sup>-1</sup>)  
485

486 The results of the analysis of variance performed for each adaptation strategy are presented in Table  
487 3. The site was the most explanatory factor of simulated yields in future weather scenarios, either  
488 considering or not adaptation strategies (Table 3). On average, simulated yields in Camargue were  
489 higher than in Lomellina, with an increase of 0.8-0.9 t ha<sup>-1</sup> (Figure 6), except for the simulations  
490 considering only the *variety* adaptation strategy (0.6 t ha<sup>-1</sup>, see Appendix G). This site effect could  
491 be explained by the highest occurrence in Lomellina, as compared to Camargue, of extremely high  
492 temperature during the summer (Appendix F), inducing more days with heat stress during ripening  
493 (Appendix E). For instance, Lomellina highlighted, for the July-August period, 58% of years where  
494 maximum temperatures exceeded 36°C (i.e., sterility threshold), while it was only 36% of the years  
495 in Camargue (Appendix F). The ranking of the importance of the different factors was consistent  
496 when considering simulations with no adaptation, *variety* and *double* adaptation (Table 3). In these  
497 situations a decreasing impact of RCP, GCM, variety group and time frame on simulated yields was  
498 observed, whereas with *sowing* adaptation the effect of variety was higher than GCM, RCP and  
499 time frame.

500 The crop model factor had a significant impact (p<0.05) on yields only with *variety* adaptation, with  
501 STICS leading to higher yields than WARM (0.3 t ha<sup>-1</sup> on average, Appendix G). The variability  
502 explained with no and with *double* adaptation was higher (R<sup>2</sup>=0.33 and 0.34, respectively; Table F)  
503 and led to lower errors of prediction (~0.95 t ha<sup>-1</sup>) as compared to the ones with *sowing* and *variety*  
504 adaptation (~1.4 t ha<sup>-1</sup>) (Table F).





505

506 Figure 6. Effects of the different factors on simulated yields in future weather scenarios. Results are  
 507 presented for simulations with no adaptation (in black) and with *double* adaptation (i.e., sowing  
 508 dates and variety, in white). The bars represent the yield difference between the two modalities, in  
 509 the order presented in the Modality column. The significance of the effects are indicated on the  
 510 right size (\*\*\*:  $p < 0.001$ ; \*\*:  $p < 0.01$ ; \*:  $p < 0.05$ ; NS: not significant, i.e.,  $p > 0.05$ )  
 511

512 The ranking of the factors' modalities was stable when considering no adaptation and *double*  
 513 adaptation strategies (Figure 6). For these strategies, the highest difference between simulated  
 514 yields was due to the GCM modality, with GISS leading to higher yields than HADGEM of about  
 515  $1.1 \text{ t ha}^{-1}$ . GISS and MIROC provided the closest yield estimation ( $0.2\text{-}0.3 \text{ t ha}^{-1}$ ), although their  
 516 difference was significant ( $p < 0.001$ ). RCP 2.6 always provided higher yields than RCP 8.5 of about  
 517  $0.5 \text{ t ha}^{-1}$  (Figure 6). The ranking of variety groups was stable for no and *double* adaptation, with  
 518 yields of longer-cycle varieties higher than shorter-cycle varieties of about  $0.4 \text{ t ha}^{-1}$ .  
 519

## 520 **4. Discussion**

### 521 **4.1. Lower yields in the future, except with adapted varieties**

522 Our main objective was to assess the future rice yield trends in Mediterranean producing countries  
523 in the context of climate change, in order to provide information to be used by stakeholders in the  
524 EU rice sector. The results indicated that, without the implementation of adaptation strategies as  
525 anticipated sowing dates and adoption of varieties with longer crop cycle, average potential rice  
526 yield in the study areas would decrease by 8% in 2030 and 12% in 2070 time frame with respect to  
527 current conditions. Such yield reduction under climate change was already highlighted on other  
528 crops in France, e.g., maize and wheat (Delecolle et al., 1995). Potential rice yields in the future  
529 would be lower than average current yield in 69% and 67% of 2030 and 2070 simulations in  
530 Camargue, and in 83% and in 84% of 2030 and 2070 simulations in Lomellina. The main factors  
531 associated with these trends are the shortening of the crop phenological phases due to temperature  
532 increase and the rising occurrence of heat stress during flowering and ripening due to temperature  
533 extremes, especially in Lomellina. The latter represents a shift of paradigm with respect to cold  
534 stress, considered as one of the major yield-limiting factor in current conditions. In our simulations,  
535 the two models consistently simulated a low average number of days with heat stress in the baseline  
536 weather (0.52 days), and an increasing trend in 2030 (1.48 days in Camargue, 3.1 days in  
537 Lomellina) and 2070 (3.4 days in Camargue, 5.9 days in Lomellina), considering together no  
538 adaptation and adaptation strategies (Appendix D, tables D1-D4).

539 However, our results strictly depend on the two modelling approaches used to simulate this process,  
540 which do not represent the whole range of available models (Krishnan et al., 2007; van Oort et al.,  
541 2014). Moreover, the only model in this study simulating the percentage of heat sterility (WARM)  
542 did not implement a heat balance at canopy level, therefore it used hourly air temperature as the  
543 driving variable for heat sterility damage. This could potentially lead to its overestimation because  
544 of the lack of consideration of transpirational cooling at canopy level, which can smooth the effects  
545 of extreme hot temperatures during flowering (Hasegawa et al., 2011; Julia and Dingkuhn, 2013;

546 Matsui et al., 2014). The emerging risk of heat stress in Lomellina is however proved by local rice  
547 growers and magazines (RisoItaliano, 2016), reporting yield losses due to spikelet sterility in 2015.  
548 Moreover, both the length of the crop cycle and the number of days with heat stress were largely  
549 correlated with simulated yields (e.g.,  $R^2 = 0.472$  and  $R^2 = 0.327$  for simulations with no adaptation  
550 and with *double* adaptation respectively). We can then infer that these factors will be major  
551 determinants of rice yield variability in the future, in accordance with findings of Muller et al.  
552 (2015) for wheat and maize – for the length of the growing season – and of Deryng et al. (2014) for  
553 maize, wheat and soybean – for the impact of heat stress.

554 Another source of uncertainty in crop model applications in climate change scenarios is due to the  
555 model formalization for simulating the CO<sub>2</sub> response, as CO<sub>2</sub> atmospheric fertilization effect could  
556 deeply affect yield predictions (Li et al., 2015). The CO<sub>2</sub> response functions implemented in the  
557 crop models used in this study (see section 2.3.1) act on the same process (i.e., RUE) and produce  
558 very similar outputs in the considered CO<sub>2</sub> range (380-660 ppm), starting to diverge at extreme high  
559 or low concentrations. This represents a limit of this study, given the simplistic and empirical  
560 representation of the CO<sub>2</sub> effect on yield as compared to more process-based Farquhar-type  
561 photosynthesis models, implemented in some rice crop simulators (e.g., Li et al., 2015; Confalonieri  
562 et al., 2016).

563 Despite these limitations, a major finding of our study is that climate change, rather than being a  
564 threat, represents an opportunity for European rice growers, as the implementation of adaptation  
565 strategies could overturn the situation, leading to an average increase of 28% in 2030 and 25% in  
566 2070 with respect to baseline mean yield levels. With the adoption of longer-cycle varieties, yields  
567 would be higher than baseline mean in the majority of cases (>76%), with however a larger  
568 frequency of lower yields in 2070, as compared to 2030, and in Lomellina, as compared to  
569 Camargue. The large differences in the yield frequency patterns in the two study areas can be  
570 explained by their climatic heterogeneity even in current conditions (Metzger et al., 2005), with  
571 Lomellina presenting more temperature extremes leading to cold (baseline) and heat (future) stress

572 than in Camargue. Such site effect, even for close locations, was already highlighted in future yield  
573 studies on rice crop (e.g., in India, Krishnan et al., 2007; in China, Xiong et al., 2009), and on other  
574 crops grown in EU, e.g. winter wheat (in Denmark and Spain, Olesen et al., 2007).

575

#### 576 **4.1.1. Factors of uncertainty for future yield predictions**

577 In this study, the sources of uncertainty were ranked according to their impact on simulated yields,  
578 aiming at evaluating their importance on models predictions. This is considered an essential step to  
579 increase the reliability of the results of climate change studies for stakeholders and policy makers  
580 (Ruiz-Ramos and Minquez, 2010).

581 The site yielded as the most important source of variability in our analysis, even if the two  
582 Mediterranean rice growing areas considered here are very close in terms of distance, and similar in  
583 average climatic pattern. However, the field of validity of our results is limited to the narrow range  
584 of the explored climatic conditions, therefore the inclusion of additional sites would certainly affect  
585 our specific results and possibly change the ranking of the sources of uncertainty. The same  
586 considerations could be done for all the other factors, even if including the two extremes of RCPs  
587 and four different GCMs strengthen our findings. A limit of this study is represented by the  
588 application of only two crop growth simulators as impact models, as it is demonstrated that they can  
589 explore a limited part of the possible variation in yield prediction (Li et al., 2015).

590 Besides the expected predominant effect of study site, RCP and GCM were found to be high  
591 sources of uncertainty for yields simulated with the different strategies. The strong effect of RCP  
592 was expected, given the use of the two IPCC extremes scenarios, whereas the importance of GCM  
593 in explaining yield variability supports the need to adopt a multi-GCM approach to manage their  
594 difference to produce input data for crop modelling studies. The effect of these two factors on  
595 potential rice yield was much higher than the one of time frame and crop model in almost all cases.  
596 While the site effect was also found by Olesen et al. (2007) as one of the main factors explaining  
597 winter wheat yields, other studies demonstrated a high effect of the crop model on future rice yield

598 quantification (e.g. Aggarwall and Mall, 2002; Matthews et al., 2003), which was however not  
599 found in our study. Olesen et al. (2007) also highlighted the magnitude of the effect of the method  
600 for scenario application, i.e., the adjustment or not of future climate series to past observed climate  
601 series. However, all these studies used different factors to simulate future yields with climate  
602 change (e.g., GCM, RCP, crop model, etc.), together with different modalities for these factors,  
603 making between-studies comparison not straightforward.

604

#### 605 **4.1.2. Effects of adaptation strategies**

606 The consideration of adaptation strategies in climate change impact studies is mandatory, as it is  
607 proved that societies, organizations and individuals will autonomously react to in response to  
608 climatic changes in the same way they have adjusted their behavior in the past (Adger et al., 2005).  
609 This study reports that without adaptation, future yields are expected to be more variable, mainly  
610 due to the higher frequency of extreme weather events (Olesen and Bindi, 2002; Xiong et al., 2009).  
611 In our study, crop-model simulations with adaptation strategies led to higher yields and yield  
612 variability, as compared to no adaptation and to baseline yields. A large increase in rice yields  
613 subsequent to variety adaptation was already shown in previous studies, e.g., in Matthews et al.  
614 (1995) with variety change towards no spikelet sterility; Krishnan et al. (2007) with variety  
615 displaying higher spikelet temperature tolerance. This last study also highlighted higher yield  
616 variability according to GCM with *variety* adaptation as compared to no adaptation. In our study,  
617 we showed that the *variety* adaptation was more efficient than the *sowing* one. Such results are in  
618 line with previous studies on rice and maize (e.g., Krishnan et al., 2007; Tingem et al., 2009; Rotter  
619 et al., 2015). There is a wide consensus on the need to evaluate the potential benefits of the  
620 implementation of adaptation strategies even in current climate, in order not to overestimate their  
621 impact in future conditions (Lobell, 2014). We performed this test by simulating the performances  
622 of the new varieties in the period 1991-2010 while keeping the original sowing date (May, 1<sup>st</sup>). We  
623 discovered that using adapted varieties in current climate lead to a major problem, which is the high

624 number of cropping seasons in which physiological maturity is not reached. The application of the  
625 new parameter sets with the thermal requirements for adapted *japonica* medium varieties leads to  
626 the completion of the crop cycle in only 47.5% and 57.5% of the years in current conditions in  
627 Camargue and Lomellina, respectively (average of the two models). This situation is even worse  
628 with the new *japonica* late varieties, as the number of years in which physiological maturity is  
629 reached is even less (2 years out of 20) in both study areas. We can thus conclude that the adoption  
630 of longer cycle varieties is beneficial in light of the rising temperature associated to climate change  
631 projections. Regarding the sowing date anticipation *per se*, thus adaptation was not tested in current  
632 conditions. Indeed, we derived future sowing dates basing on current climate, considering the  
633 number of times when the weekly average of average temperature is above 10°C from March 1<sup>st</sup> to  
634 May 1<sup>st</sup>. Therefore, applying this rule in current climate leads to the sowing date already used to  
635 perform baseline simulations.

636

#### 637 **4.2. Methodological choices**

638 The reported ranges of variation between future and current yields strongly vary in literature and are  
639 affected by many sources of uncertainty, including the choice of the crop models, the climate  
640 change scenario, the study period and the study region (Hawkins and Sutton, 2009). In their review  
641 on the impacts of climate change on rice production, Matthews and Wassman (2003) reported that,  
642 according to the results of the IRRI/EPA project, future yield levels in Asia would range from -  
643 12.8% to +6.5% depending on the considered combination of the rice model and of the GCM.  
644 These findings support the adoption of a multi-crop model and multi-scenario approach to quantify  
645 the uncertainty associated to the assessment of the climate change impacts on crop production. In  
646 this context, our methodological choices focused on the adoption of two crop models, which were  
647 already used to reproduce rice growth and development in the study areas, and on the use of the two  
648 extreme IPCC-RCP scenarios (IPCC's Fifth Assessment Report), as projected by four GCM in the  
649 short and long terms, using the methodology developed by Cappelli et al. (2015).

650 The choice of using four GCMs out of the 39 available in the study area (Zubler et al., 2016) could  
651 represent a limit of this study, because we do not explore the whole range of variability in climate  
652 predictions. However, the extensive review performed by Burke et al. (2012), including nearly 200  
653 published papers in peer-reviewed and working paper series, reports three as the median number of  
654 GCMs applied to take into account the uncertainty in climate predictions on agricultural impact  
655 studies. Even if the GCMs' selection in our study was based on a random criterion, Zubler et al.  
656 (2016) demonstrated via hierarchical cluster analysis that the four GCMs we chose fall in separate  
657 clusters based on their temperature and precipitation outputs (corresponding to our study area), with  
658 GISS and NorESM presenting the largest dissimilarity. Moreover, Burke et al. (2012) showed that  
659 the GCMs developed by the Hadley Centre (HADgem) is the most used in available literature (more  
660 than 50% of the papers), and we included it in our analysis. Therefore, our sampling of available  
661 GCMs to only four well-separated GCMs can be considered a reasonable choice, although we do  
662 not explore the whole range of available variability.

663 The biophysical adaptation strategies developed here – the anticipation of the sowing dates and the  
664 adoption of varieties with a longer cycle – are commonly tested in crop simulation studies aiming at  
665 assessing climate change impacts on crop production (e.g., Deryng et al., 2011; Wang et al., 2012).  
666 They can be considered autonomous adaptations (Olesen et al., 2011), as they represent short-term  
667 adjustments that are commonly implemented by farmers. We based our adaptation strategies on  
668 specific rules derived from the future climate projections used in our study, rather than applying a  
669 fixed number of days to shift sowing dates (e.g., Moradi et al., 2013) or a fixed increase of thermal  
670 time requirements to develop adapted varieties (e.g., Tingem and Rivington, 2009; Tao and Zhang,  
671 2010). Our rationale was conservative, because we defined the future sowing dates basing on the  
672 relationships between the sowing period adopted by rice growers in the study areas and the current  
673 weather conditions. This led to a biophysical meaningful and literature derived rule, which was then  
674 applied to determine the new sowing dates to initialize crop model simulations in the future climate.  
675 The same logic was followed to plausibly determine the possible adapted varieties to be included in

676 the simulation experiment. We started from expert knowledge of rice cropping systems in the two  
677 study areas to derive a standard duration of the crop cycle for medium and late varieties (140 and  
678 160 days, respectively). The modification of model parameters to simulate adapted varieties  
679 involved only the thermal requirements to reach flowering and maturity stage, which were set to  
680 1180 and 453 growing degree days (GDD, °C d<sup>-1</sup>) for WARM, and to 1170 and 610 GDD for  
681 STICS. The coherence of these new values with available genetic material is proved by the very  
682 similar values calibrated by Confalonieri et al. (2009) for Italian *indica* varieties with the WOFOST  
683 model (1170 °C d<sup>-1</sup> from emergence to anthesis and 370 °C d<sup>-1</sup> from anthesis to maturity). Similar  
684 thermal time requirements were also set by Li et al. (2015) for the crop models SAMARA  
685 (Dingkuhn et al., 2011) and STICS, which were calibrated using reference data collected on *indica*  
686 varieties in four sentinel datasets in Asian countries. The ratio between the duration of the  
687 emergence-flowering and flowering-maturity periods in our new varieties was kept as in current  
688 varieties, and it was on average 38% for WARM and 34% for STICS. This is also consistent with  
689 the above-cited studies, in which it ranged between 34% and 46%. Then, the varieties designed in  
690 this study toward the use in the near- and medium future could already be available for such  
691 adaptation, making it possible to improve future rice yields in the Mediterranean areas.

692

## 693 **Conclusions**

694 The variability of global rice production in a changing climate is a hot and controversial topic, and  
695 it still needs further investigation because of its prominence as a staple food in Asian top producing  
696 countries. Despite the huge number of crop modelling studies dealing with the impact of global  
697 warming on rice in tropical climates, the future trends of rice productions in Mediterranean areas is  
698 scarcely investigated and even more uncertain. Our findings indicate that the European rice sector  
699 has the potential to enhance current production levels, taking advantage of the increase of ambient  
700 CO<sub>2</sub> concentration and air temperature during the growing season associated with climate change  
701 conditions. The anticipation of rice sowing dates and even more the adoption of varieties with a



702 longer crop cycle then represent effective adaptation strategies to increase rice yields and in turn  
703 farmers' income in the considered European rice areas in the short and long term.

704

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712

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