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Simone Bregaglio[1,*,§], Laure Hossard[2,*], Giovanni Cappelli[1,§], Remi Resmond[2], Stefano Bocchi[3], Jean-Marc Barbier[2], Françoise Ruget[4], Sylvestre Delmotte[2]

[1]: Council for Agricultural Research and Economics, Agriculture and Environment Research Centre, via di Corticella 133, I-40128 Bologna, Italy

[2]: INRA, UMR951 Innovation, F-34060 Montpellier, France

[3]: Università degli Studi di Milano, DiSAA, via Celoria 2, 20133 Milan, Italy

[4]: INRA, UMR1114 Environnement Méditerranéen et Modélisation des Agro-Hydrosystèmes, F-84914 Avignon Cedex 9, France

[§]: The research of this paper was carried out while the author was at Università degli Studi di Milano, DiSAA, via Celoria 2, 20133 Milan, Italy

[*] These two authors contributed equally to this study. Corresponding authors:

Simone Bregaglio Tel.: +39 051 6316847; E-mail: simoneugomaria.bregaglio@crea.gov.it

Laure Hossard Tel.: +33 4 99 61 20 19; E mail: laure.hossard@inra.fr

Abstract

The future of global rice productions in top producing countries is undermined by the impact of climate change threatening food security in the near future. In those European Mediterranean areas where rice is cultivated, this peculiar cropping system plays a crucial role in terms of sociocultural and ecological issues, and the climate change impact is still scarcely investigated. In this study, we explored the future trends of potential rice yields in the region considering the multiple sources of uncertainty associated with climate and yield predictions. Two rice crop models (STICS and WARM) were calibrated using 20 field experiments carried out in two main European rice producing areas – i.e., the Italian Lomellina and the French Camargue. These models were then applied under a range of climate change scenarios in 2030 and 2070 time frames, considering projections from the combination of four General Circulation Models and two extreme Representative CO_2 Concentration Pathways (RCP 2.6 and 8.5). We compared the simulated yield levels with no adaptation, and designed adaptation strategies based on the anticipation of sowing date and the adoption of varieties with longer crop cycle. Our results showed that with no adaptation yields would decrease on average by 8% in 2030 and 12% in 2070 in Camargue and Lomellina, respectively. Future simulated yields in the two areas were lower than in the baseline in 67% (Camargue) and 84% (Lomellina) of the cases. The implementation of both adaptation strategies proved to be effective in reversing the situation, leading to an average yield increase of 28% and 25% in 2030 and 2070, respectively. The associated probability of lower yields than in current conditions was 24% in the two sites. Despite the uncertainty in predictions, mainly related to site, GCM and RCP, our findings indicate that the European rice sector has the potential to enhance current production levels in a changing climate, if longer cycle varieties will be grown in Mediterranean rice areas.

Keywords

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

Introduction

The effects of climate change on the future rice (*Oryza sativa* L.) production is still under debate in the three top producing countries – China (Tao and Zhang, 2013), India (Aggarwal and Mall, 2002) and Indonesia (Naylor et al., 2007) – due to the counterbalance between the beneficial effect of rising atmospheric CO_2 concentration and the exacerbation of abiotic stresses on crop growth, such as heat (Baker et al., 1992), drought (Wassmann et al., 2009) and salinity (Redman et al., 2011). The available estimates are discordant, and range between an increase of 10-15% in 2020 (Tao and Zhang, 2013) to 7-10% yield losses per every 1 °C increase in air temperature (Peng et al., 2004; Krishnan et al., 2007). Given the leading role of rice as a staple food for humans (Fitzgerald et al., 2008; Soora et al., 2013) and the need of doubling crop production by 2050 to meet the projected demand of the global population (Ray et al., 2013), this research question is in the spotlight, and efforts are still needed to deepen current knowledge. In the meanwhile, rice growers and stakeholders of the rice sector are already implementing adaptation strategies, ranging from individual autonomous local reactions (Dharmarathna et al., 2014) to planned policy interventions (Huang et al., 2015), in order to alleviate the negative impacts of climate change in the main producing environments (Howden et al., 2007).

Nevertheless, less research has been devoted to analyse the consequences of climate change on rice production in Europe (EU), where rice is the 6^{th} most produced cereal, with almost 4 million tons on about 650,000 ha in 2013, for an average yield of 6 t ha^{-1} (FAOSTAT, 2014). Although not being a staple food crop in EU, rice plays a pivotal sociocultural (Picazo-Tadeo et al., 2009) and ecological (Longoni, 2012) role in several Mediterranean countries, where the human consumption is steadily increasing (Ferrero and Tinarelli, 2007; Worldatlas, 2016). Italy, Spain, Greece, Portugal and France are the five top European producing countries, and present a higher per capita annual rice consumption (6-18 kg $year^{-1}$) than in non-producing northern countries (3.5-5.5 kg $year^{-1}$, Maclean et al., 2002). The typical European rice production system presents paddy cultivation under continuous flooding during most part of the crop cycle (Hill et al., 1991), and water drainages to allow rooting, top-dressing fertilization, herbicide spraying and harvesting (Fusi et al., 2014). Cold temperatures are the main environmental constraint to rice production in Mediterranean countries (Jena and Hardy, 2012). Damages to rice crop due to low temperatures can occur at any growth stage, being particularly severe at sowing, when they can undermine the germination capacity and the establishment of rice plants (Ferrero and Tabacchi, 2002), and during microsporogenesis stage (Dingkuhn et al., 1995), when high diurnal temperature ranges can increase the risk of pollen sterility (Russo and Callegarin, 1997). With increased temperatures due to climate change, heat stress could be more frequent on temperate rice crop. Recent findings in rice physiology indicate that heat stress causing sterility in the exerted part of the panicle is likely to occur even in Mediterranean countries, especially in warm and humid years (Julia and Dingkuhn, 2013).

The complex effects of global warming and CO_2 increase on rice growth in Mediterranean countries comprise both detrimental and beneficial effects. The meta-analysis carried out by Wang et al. (2015) reports a percentage yield increase of 24.5% at 660-699 ppm, which is mainly associated to an increase in the number of panicles and grains per plant. Likewise, available free air CO_2 enrichment experiments allowed to quantify the atmospheric fertilization benefits on temperate rice yields in the range 7-15% at 586-645 μmol mol^{-1} for *japonica* type varieties (Kim et al., 2003), which are the most widespread in EU (Confalonieri and Bocchi, 2005). The increase in air temperature can lead to the decreased occurrence of cold sterility events, which currently are a major constraint to European rice yield. Potential positive effects of higher temperature are also related to the anticipation and the extension of the growing season length (Peng et al., 1995), which can favour the cultivation of longer cycle varieties, and to the improvement of plant photosynthetic rates. The latter will probably increase because of the thermal requirements of this tropical crop (Borjigidai et al., 2006) and due to the higher CO_2 concentration in the atmosphere. The temperature increase can also cause detrimental effects on future rice production, such as the shortening of the crop cycle, especially of the grain filling period (Matthews and Wassmann, 2003) and the increased risk of heat sterility during pollination (Hirabayashi et al., 2015), and the loss of sink activity of the panicle (Kim et al., 2011). As for other driving variables of the biophysical system (Dieleman et al., 2012), the predominance of the complex interactions on the simple additive effects between temperature and CO_2 in affecting crop production, constitutes an additional source of variability in the future trends of rice yield (Long et al., 2006).

The complex array of uncertainties connected with the study of the impact of climate change on crop yield – including observed climate inputs, future CO_2 concentrations, climate model outputs and projected impacts (Challinor et al., 2009) – makes current projections inherently highly uncertain (Godfray et al., 2010; Asseng et al., 2013). An effective and standard methodological framework to quantify these multiple sources of uncertainty is still lacking (Burke et al., 2015), even if this became a topic by itself (Wesselink et al., 2015). Moreover, the ranking of their importance is considered a required milestone to improve the understanding of the real impacts of climate change, and to enhance the credibility of climate change studies for policy makers (Ruiz-Ramos and Minquez, 2010).

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

This paper aims at exploring the main trends of future Mediterranean rice yields, and to quantify and rank the multiple sources of uncertainty related to climate and yield predictions. Two rice crop models were applied in two main European rice producing areas - the Italian Lomellina and the French Camargue - to simulate potential rice growth and development in current conditions and under a wide range of climate change scenarios, considering projections of four General Circulation Models (GCM) and two contrasting Representative CO_2 Concentration pathways (RCP; IPCC, 2014).

1. Materials and methods

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

Figure 1. Activities performed in this study, with associated synthetic input information. Stat: statistical analysis on the simulation outputs.

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

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

2.1 Characterization of the study areas

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

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

The typical agricultural management of rice fields presents direct seeding and continuous flooding until milky ripening stage, with two-three water drainages during the growing season to promote rooting and before the application of weed control products and top dress fertilizers (mainly urea, average dose 150 kg ha^{-1}), which are usually split at sowing, tillering and panicle differentiation stage. The most widespread rice varieties mainly belong to the *japonica* ecotype, with main differences in the duration of the growing cycle.

Weed infestation and cold temperatures are among the main constraints to rice production during the crop establishment phase in both French and Italian rice areas, whereas spikelet sterility due to cold air irruptions around flowering (Biologische Bundesanstalt, Bundessortenamt und CHemische Industrie, BBCH codes 61-69) often occurs leading to yield losses (Mariani et al., 2009).

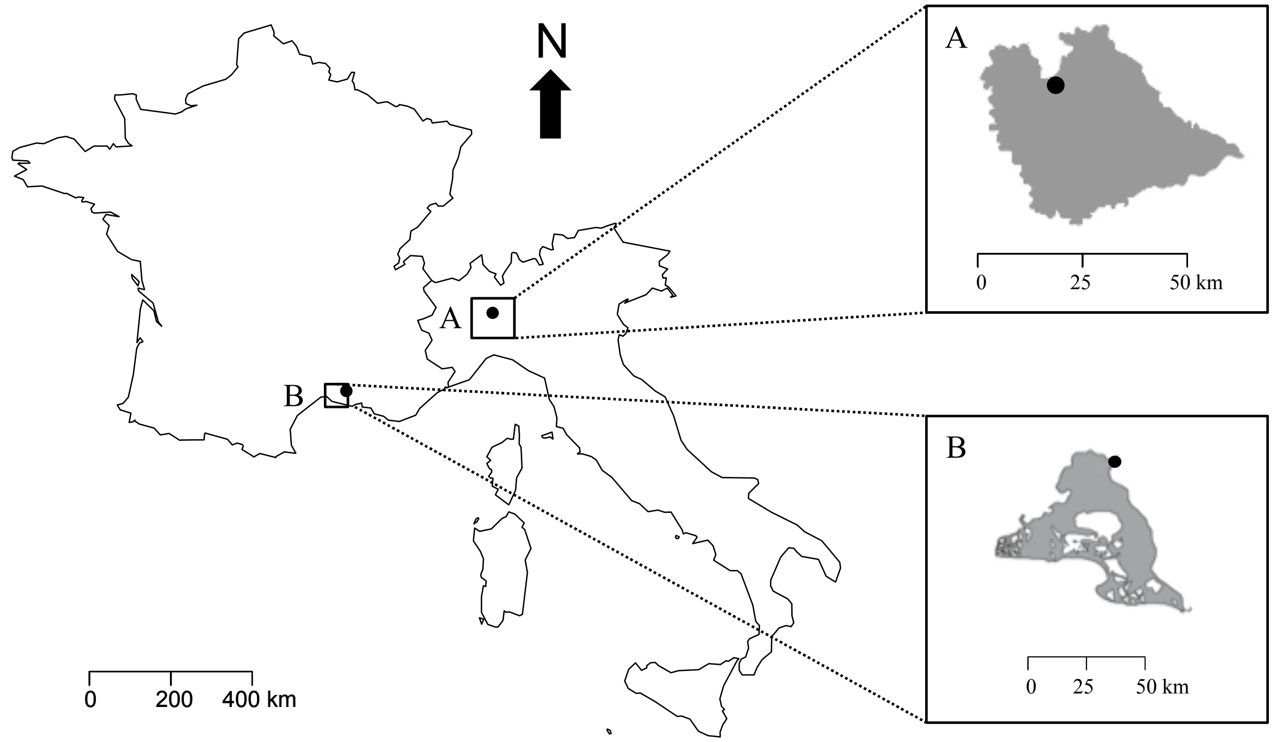

Figure 2. Location of the two study areas (A : Lomellina, B : Camargue). Black dots represent the locations of the meteorological stations

2.2 Current and future weather scenarios

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

d^{-1}), average wind speed ($m\ s^{-1}$) and evapotranspiration ($mm\ d^{-1}$). These baseline data and four GCM realizations of two contrasting RCP were used to generate the 20-years future weather series to consider a range of plausible impacts of the changes in atmospheric composition due to the effects of technology, economy, lifestyle, and policy development on climate (IPCC, 2014). Two future time frames were considered, referring to the near (2030) and long-term (2070) futures.

The GCM were randomly selected among the ones included in the Coupled Model Intercomparison Project (CMIP5, http://cmip-pcmdi.llnl.gov/cmip5/): the Norwegian Earth System Model (NOResm, Tjiputra et al., 2013), the Model for Interdisciplinary Research on Climate (MIROC-ESM, Watanabe et al., 2011), the Hadley Centre Global Environmental Model version 2 (HadGEM2-ES, Collins et al., 2011), and the GCM developed by the Goddard Institute for Space Studies (GISS-ES, Schmidt et al., 2006).

The two extremes of the RCP of greenhouse gas (GHG) concentration proposed by IPCC were used in this study: the RCP 2.6, which assumes a peak of global annual GHG emissions between 2010-2020 and a radiative increase up to 2.6 $W\ m^{-2}$, with CO_2 concentration reaching 420 ppm in 2100, and the RCP 8.5, projecting a continuous rise of GHG emissions throughout the 21st century with a radiative increase of 8.5 $W\ m^{-2}$, with CO_2 concentration reaching 936 ppm in 2100 (IPCC, 2014). The CO_2 concentration for baseline conditions was set to 382 ppm, and the future CO_2 concentrations used as input in the simulation experiment were 438 ppm (2030) and 444 ppm (2070) for RCP 2.6, and 438 ppm (2030) and 660 ppm (2070) for RCP 8.5 (IPCC, 2013).

The average monthly absolute anomalies of temperature and precipitation in the period 2021-2040 for 2030 time frame, and 2061-2080 for 2070 time frame (difference or ratio between the future and the present value of the variable; Déqué et al., 2007), corresponding to each GCM × RCP combination, were downloaded from the Program for Climate Model Diagnosis and Intercomparison data portal (https://pcmdi.llnl.gov/search/cmip5/). They were then used to modulate the parameters of the CLIMAK weather generator (Danuso, 2002), in order to generate the 20-years of future weather series to be used in the simulation experiment, following the procedure used by Confalonieri et al. (2013), Cappelli et al. (2015) and Paleari et al. (2015). In this simulation experiment 34 weather series of 20-years were used, as the sum of the 2 baseline for Lomellina and Camargue and of 32 future weather scenarios, as the product of 2 RCP × 4 GCM × 2 future time frames × 2 study areas.

2.3. Simulation experiment design

2.3.1. Crop simulation models

The simulation of rice growth and development in baseline and future weather scenarios was performed at potential production level, i.e., defined by the genotype of the rice variety and by solar radiation, temperature and CO_2 concentration (De Wit and Penning de Vries, 1982; Rabbinge, 1993). We did not consider the limiting effects of water and nutrient availability on yield – the attainable production level – because rice-cropping systems are flooded and receive generally a high fertilization rate in both areas. We used the generic crop model STICS (Brisson et al., 1998) adapted for rice (Ruget et al., 2016) and the rice model WARM (Confalonieri et al., 2009) to perform the simulation experiment, as these two models were developed under temperate conditions. Although they both simulate crop phenological development as a function of thermal time accumulation and share the main concept of radiation use efficiency (RUE, g MJ^{-1}, Warren Wilson, 1967) to reproduce biomass growth, they markedly differ in the formalization of the algorithms used to mimic crop growth and respond to weather input data (Table 1). Main differences between the two models are the time step to compute rice growth and development – hourly for WARM and daily for STICS – and the formalization of the plant processes leading to the dynamic increase of leaf area index and to the partitioning of assimilates to leaves, stems and panicles. Hourly data of air temperature and global radiation as input for the WARM model were estimated according to Campbell (1985) and Chen et al. (1999) starting from daily data.

The WARM model daily updates the leaf area index (m^2 m^{-2}) by multiplying the daily increase of leaves biomass (kg m^{-2}) by the specific leaf area (m^2 kg^{-1}), and computes leaves senescence as driven by a threshold of thermal time, whereas STICS calculates the leaf area index increase as mediated by air temperature. The partitioning pattern in STICS is driven by a dynamic harvest index, which is upper limited by the product of grain numbers by maximum grain weight, whereas in WARM it depends solely on crop development stage, with the weight of reproductive organs starting to grow after panicle initiation stage. The maximum value of radiation use efficiency is modulated in both models by temperature, radiation, development stage and CO_2 concentration, according to different modelling approaches. The two models differ in the simulation of the impacts of cold and heat stress on rice yield. The WARM model simulates a reduction of spikelet fertility due to cold and heat stresses acting in a critical time window around flowering, whereas STICS stops the grain filling process in post-anthesis while decreasing the number of grains during the ripening period as a response to low and high temperatures. The beneficial effect of increasing atmospheric CO_2 in future climate scenarios is simulated by the two models with empirical functions (Appendix B).

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

Process	Sub process	WARM	STICS
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_2 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

2.3.2. Models' calibration in current weather conditions

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

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

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

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

2.3.3. Simulations in current and future weather scenarios

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

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

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

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

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

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

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

2.4 Statistical analysis

Uncertainties in yield predictions attributable to the GCM, the RCP, and the crop model were evaluated with an analysis of variance together with the effects of the time frame, the site and the variety group. The contribution of each source of uncertainty was assessed by the Mean Squared Error (MS), calculated as the sum of squares divided by the associated number of degrees of freedom (df). MS was used to compare the contributions of the different factors to the total variability in simulated rice yields (the highest the MS of a factor, the highest its contribution). The significance of each factor was then evaluated using F-tests. Finally, the goodness-of-fit of the model was assessed by the adjusted R^2 and the size of the errors in the residuals (Root Mean Square Error, RMSE). All analyses were performed with the R software version 3.2.3 (R Development core team, 2015). The analysis of variance was performed using the 'aov' function and the RMSE was calculated using the 'rmse' function of package hydroGOF (Zambrano-Bigiarini, 2014).

3. Results

3.1. Future trends of rice yield

3.1.1. Yield dynamics

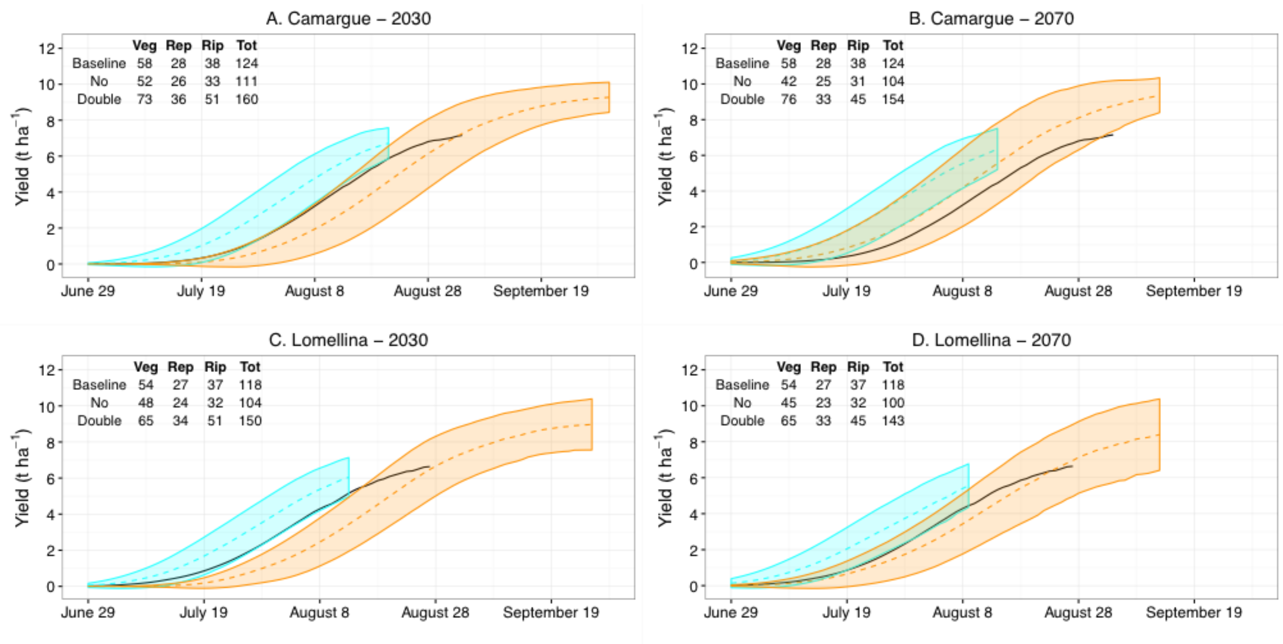

Figure 3. Dynamic of simulated panicle biomass growth from panicle initiation to physiological maturity in baseline (black line) and in future weather scenarios, considering no adaptation (cyan) and the implementation of double adaptation (considering together *sowing* and *variety* adaptations, orange).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

The results related to yield dynamics simulated under current/climate change scenarios are presented in Figure 3. In 2030, the simulation of rice phenological development in both sites with no adaptation (Figure 3A, C) led to a shortening of the crop cycle of 13.5 days due to an anticipation of the main rice growth stages (-6 days for vegetative period, -2.5 days for reproductive period and -5 days for the ripening period). In 2070, the further anticipation of the main phenological phases (-9.5 days for vegetative period, -3.5 days for reproductive period and -6 days for ripening) led to a shortening of the whole crop cycle of 19 days. The combined effect of the anticipation of sowing dates and the adoption of varieties with higher thermal requirements (*double* adaptation) determined a longer duration of the main phenological stages and their delayed occurrence with respect to both no adaptation and baseline simulations (Figure 3B, D). This effect was clearer in 2030 (+13 days for vegetative period, +7.5 days for reproductive period and +13.5 days for ripening), whereas in 2070 the increase of air temperature smoothed these differences, especially for reproductive (+5.5 days) and grain filling (+7.5 days) period. Therefore, the average duration of the whole crop cycle was longer in 2030 (155 days) than in 2070 (148.5 days). On average, the impact of climate change on the shortening of the crop cycle was similar in the two case studies, with -32 days in 2030 and -30 days in 2070 in Lomellina and -36 days in 2030 and -25 days in Camargue.

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

3.1.2. Yield distribution

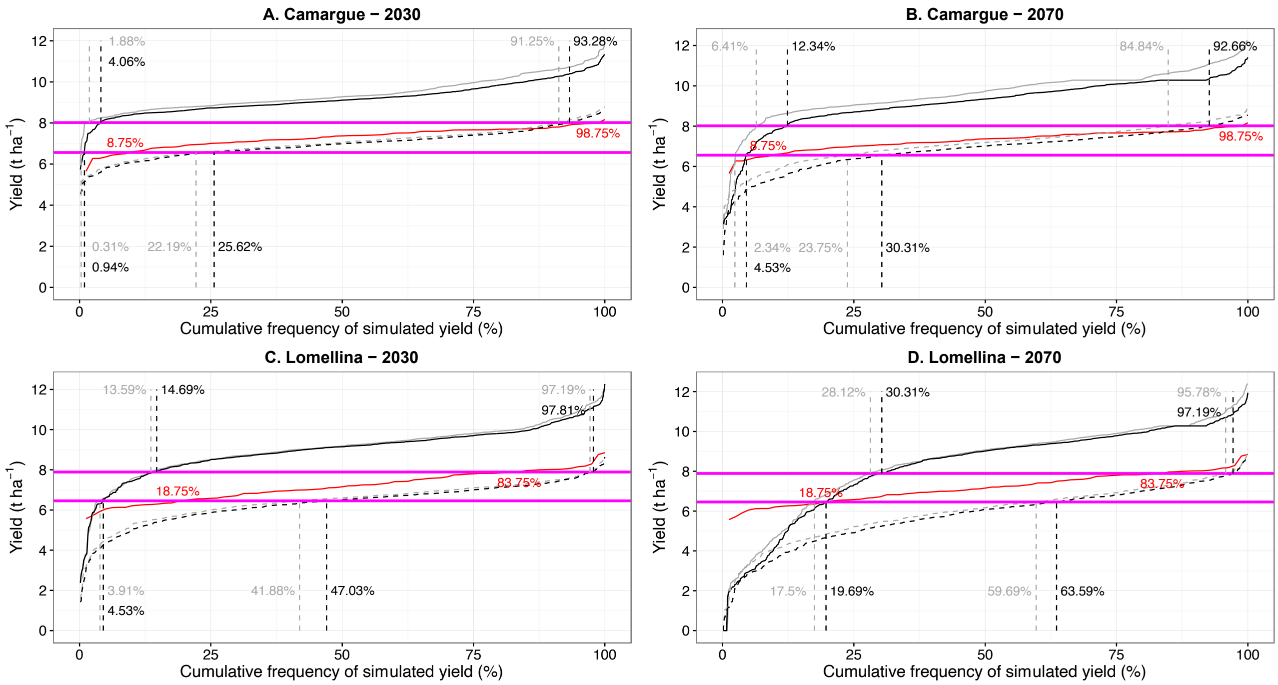

Figure 4. Cumulative frequency distribution of simulated yields in site-specific baseline and in future weather scenarios with no adaptation and with the implementation of the three adaptation strategies, as compared to the simulations in baseline conditions for the two sites (Camargue, A and B; Lomellina, 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 ±10% mean baseline yield, respectively.

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^{-1} to 8.6 t ha^{-1} in 2030 and from 1.6 t ha^{-1} to 8.5 t ha^{-1} in 2070. In Lomellina, simulated yields were even lower, ranging from 1.4 t ha^{-1} to 8.6 t ha^{-1} in 2030 and from 0 t ha^{-1} to 8.8 t ha^{-1} 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^{-1} and 11.8 t ha^{-1} in 2030, and between 3 t ha^{-1} and 12.2 t ha^{-1} in 2070 in Camargue. In Lomellina, simulated yields were in the range 2.5-12.2 t ha^{-1} in 2030 and 0-12.4 t ha^{-1} in 2070. The almost total yield loss (around 0 t ha^{-1}) simulated in 2070 corresponded to the occurrence of massive heat stress due to extreme weather conditions, which were more frequent in Lomellina than in Camargue in almost all of simulations (90%) for each adaptation strategy (mean difference of 4 days for *double* adaptation, and of 3 days for no, *sowing* and *variety* adaptation; see Appendix E). We refer here to “heat stress” as the combined effects of panicle sterility simulated by WARM and of the reduction of grain number and weight simulated by STICS.

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

3.2 Quantifying yield uncertainty due to climate changes projections

3.2.1. Overview of the magnitude of each factor

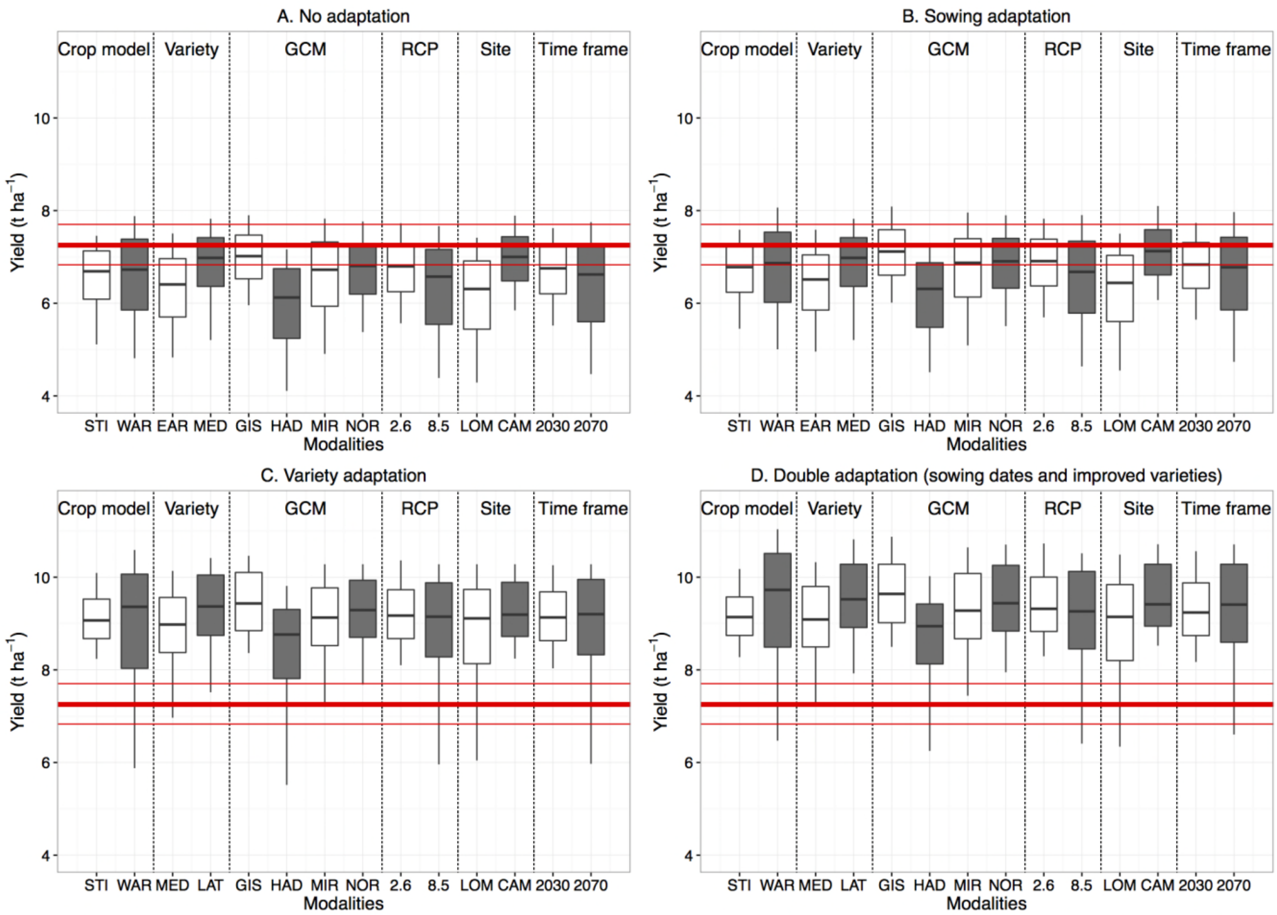

Figure 5. Boxplots of final yields simulated according to each modality (x-axis) of the six factors considered here (crop model, group of varieties, GCM, RCP, site and time frame). Plotted values refer to simulations with no adaptation (A), according to the implementation of *sowing* (B) and *variety*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

Figure 5 summarizes the effects of each factor by synthetizing its distribution (10, 25, 50, 75 and 90^{th} quantiles) for each factor modality (e.g., STICS and WARM modalities for the crop model factor). The ranking of the modalities' median values was stable for every factor whatever the adaptation strategy considered, whereas the associated yield variability differed according to the different modalities of each factor (Figure 5). Median yield values and yield variability simulated by WARM were higher than for STICS, this difference increasing with *variety* and *double* adaptation (Figure 5). The adoption of varieties with a longer cycle had an opposite impact on the yield variability simulated by the two models, with WARM increasing and STICS reducing the yield variability. The varieties with longer cycles displayed higher yields than early varieties, consistently between the four tested strategies. The yield variability associated to GCM was similar between the four modalities.

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

3.2.2. Ranking the components of uncertainty

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

		No adaptation		*Sowing*		*Variety*		*Double*	
Factor	d.f.	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^2		0.329		0.339		0.173		0.187	
RMSE		0.976		0.921		1.440		1.424	

d.f. : number of degrees of freedom ; MS : Mean Squared Error ; RMSE : Root Mean Squared Error (in t ha^{-1})

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

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

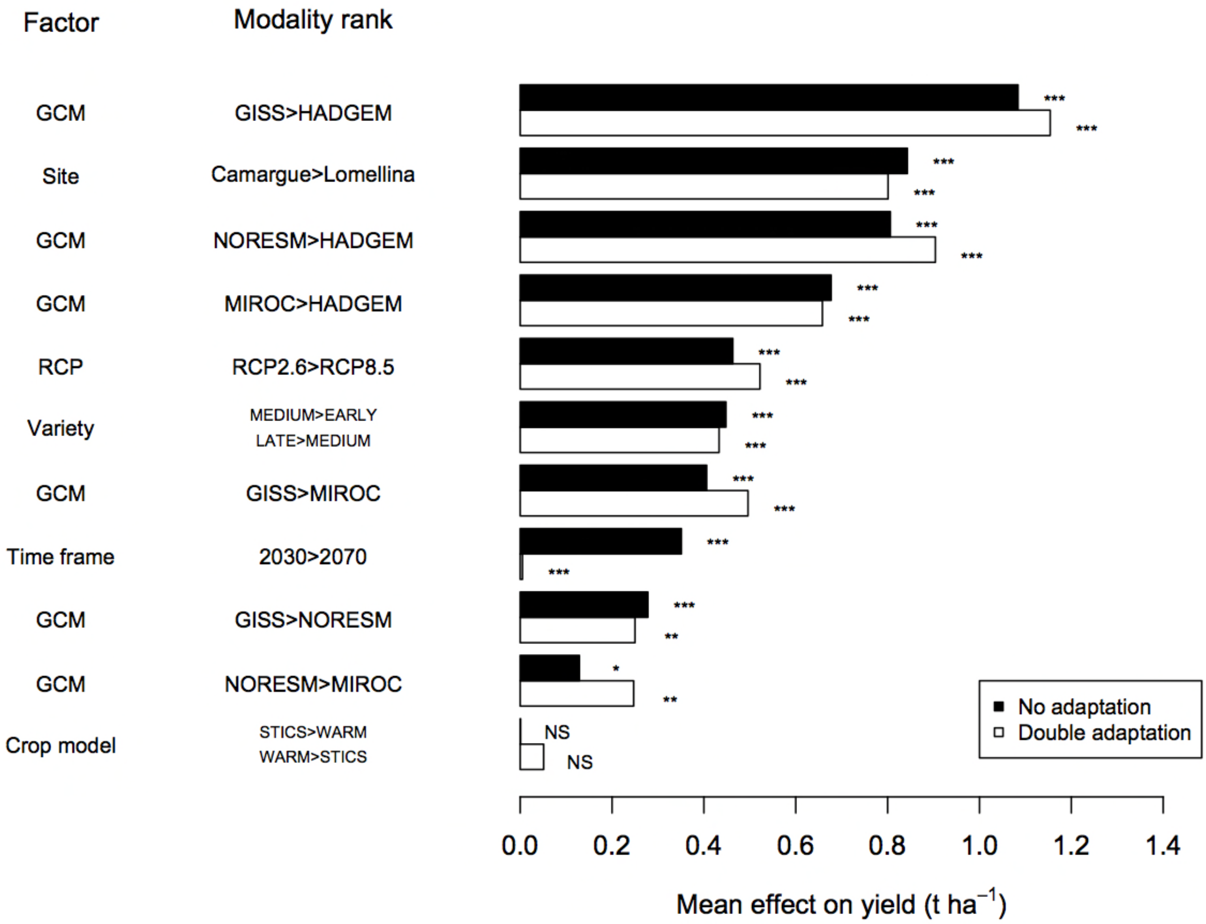

Figure 6. Effects of the different factors on simulated yields in future weather scenarios. Results are presented for simulations with no adaptation (in black) and with *double* adaptation (i.e., sowing dates and variety, in white). The bars represent the yield difference between the two modalities,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

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

4. Discussion

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

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

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

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

Another source of uncertainty in crop model applications in climate change scenarios is due to the model formalization for simulating the CO_2 response, as CO_2 atmospheric fertilization effect could deeply affect yield predictions (Li et al., 2015). The CO_2 response functions implemented in the crop models used in this study (see section 2.3.1) act on the same process (i.e., RUE) and produce very similar outputs in the considered CO_2 range (380-660 ppm), starting to diverge at extreme high or low concentrations. This represents a limit of this study, given the simplistic and empirical representation of the CO_2 effect on yield as compared to more process-based Farquhar-type photosynthesis models, implemented in some rice crop simulators (e.g., Li et al., 2015; Confalonieri et al., 2016).

Despite these limitations, a major finding of our study is that climate change, rather than being a threat, represents an opportunity for European rice growers, as the implementation of adaptation strategies could overturn the situation, leading to an average increase of 28% in 2030 and 25% in 2070 with respect to baseline mean yield levels. With the adoption of longer-cycle varieties, yields would be higher than baseline mean in the majority of cases (>76%), with however a larger frequency of lower yields in 2070, as compared to 2030, and in Lomellina, as compared to Camargue. The large differences in the yield frequency patterns in the two study areas can be explained by their climatic heterogeneity even in current conditions (Metzger et al., 2005), with Lomellina presenting more temperature extremes leading to cold (baseline) and heat (future) stress than in Camargue. Such site effect, even for close locations, was already highlighted in future yield studies on rice crop (e.g., in India, Krishnan et al., 2007; in China, Xiong et al., 2009), and on other crops grown in EU, e.g. winter wheat (in Denmark and Spain, Olesen et al., 2007).

4.1.1. Factors of uncertainty for future yield predictions

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

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

Besides the expected predominant effect of study site, RCP and GCM were found to be high sources of uncertainty for yields simulated with the different strategies. The strong effect of RCP was expected, given the use of the two IPCC extremes scenarios, whereas the importance of GCM in explaining yield variability supports the need to adopt a multi-GCM approach to manage their difference to produce input data for crop modelling studies. The effect of these two factors on potential rice yield was much higher than the one of time frame and crop model in almost all cases. While the site effect was also found by Olesen et al. (2007) as one of the main factors explaining winter wheat yields, other studies demonstrated a high effect of the crop model on future rice yield quantification (e.g. Aggarwall and Mall, 2002; Matthews et al., 2003), which was however not found in our study. Olesen et al. (2007) also highlighted the magnitude of the effect of the method for scenario application, i.e., the adjustment or not of future climate series to past observed climate series. However, all these studies used different factors to simulate future yields with climate change (e.g., GCM, RCP, crop model, etc.), together with different modalities for these factors, making between-studies comparison not straightforward.

4.1.2. Effects of adaptation strategies

The consideration of adaptation strategies in climate change impact studies is mandatory, as it is proved that societies, organizations and individuals will autonomously react to in response to climatic changes in the same way they have adjusted their behavior in the past (Adger et al., 2005). This study reports that without adaptation, future yields are expected to be more variable, mainly due to the higher frequency of extreme weather events (Olesen and Bindi, 2002; Xiong et al., 2009). In our study, crop-model simulations with adaptation strategies led to higher yields and yield variability, as compared to no adaptation and to baseline yields. A large increase in rice yields subsequent to variety adaptation was already shown in previous studies, e.g., in Matthews et al. (1995) with variety change towards no spikelet sterility; Krishnan et al. (2007) with variety displaying higher spikelet temperature tolerance. This last study also highlighted higher yield variability according to GCM with *variety* adaptation as compared to no adaptation. In our study, we showed that the *variety* adaptation was more efficient than the *sowing* one. Such results are in line with previous studies on rice and maize (e.g., Krishnan et al., 2007; Tingem et al., 209; Rotter et al., 2015). There is a wide consensus on the need to evaluate the potential benefits of the implementation of adaptation strategies even in current climate, in order not to overestimate their impact in future conditions (Lobell, 2014). We performed this test by simulating the performances of the new varieties in the period 1991-2010 while keeping the original sowing date (May, 1st). We discovered that using adapted varieties in current climate lead to a major problem, which is the high number of cropping seasons in which physiological maturity is not reached. The application of the new parameter sets with the thermal requirements for adapted *japonica* medium varieties leads to the completion of the crop cycle in only 47.5% and 57.5% of the years in current conditions in Camargue and Lomellina, respectively (average of the two models). This situation is even worse with the new *japonica* late varieties, as the number of years in which physiological maturity is reached is even less (2 years out of 20) in both study areas. We can thus conclude that the adoption of longer cycle varieties is beneficial in light of the rising temperature associated to climate change projections. Regarding the sowing date anticipation *per se*, thus adaptation was not tested in current conditions. Indeed, we derived future sowing dates basing on current climate, considering the number of times when the weekly average of average temperature is above 10°C from March 1st to May 1st. Therefore, applying this rule in current climate leads to the sowing date already used to perform baseline simulations.

4.2. Methodological choices

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

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

The biophysical adaptation strategies developed here – the anticipation of the sowing dates and the adoption of varieties with a longer cycle – are commonly tested in crop simulation studies aiming at assessing climate change impacts on crop production (e.g., Deryng et al., 2011; Wang et al., 2012). They can be considered autonomous adaptations (Olesen et al., 2011), as they represent short-term adjustments that are commonly implemented by farmers. We based our adaptation strategies on specific rules derived from the future climate projections used in our study, rather than applying a fixed number of days to shift sowing dates (e.g., Moradi et al., 2013) or a fixed increase of thermal time requirements to develop adapted varieties (e.g., Tingem and Rivington, 2009; Tao and Zhang, 2010). Our rationale was conservative, because we defined the future sowing dates basing on the relationships between the sowing period adopted by rice growers in the study areas and the current weather conditions. This led to a biophysical meaningful and literature derived rule, which was then applied to determine the new sowing dates to initialize crop model simulations in the future climate. The same logic was followed to plausibly determine the possible adapted varieties to be included in the simulation experiment. We started from expert knowledge of rice cropping systems in the two study areas to derive a standard duration of the crop cycle for medium and late varieties (140 and 160 days, respectively). The modification of model parameters to simulate adapted varieties involved only the thermal requirements to reach flowering and maturity stage, which were set to 1180 and 453 growing degree days (GDD, °C d^{-1}) for WARM, and to 1170 and 610 GDD for STICS. The coherence of these new values with available genetic material is proved by the very similar values calibrated by Confalonieri et al. (2009) for Italian *indica* varieties with the WOFOST model (1170 °C d^{-1} from emergence to anthesis and 370 °C d^{-1} from anthesis to maturity). Similar thermal time requirements were also set by Li et al. (2015) for the crop models SAMARA (Dingkuhn et al., 2011) and STICS, which were calibrated using reference data collected on *indica* varieties in four sentinel datasets in Asian countries. The ratio between the duration of the emergence-flowering and flowering-maturity periods in our new varieties was kept as in current varieties, and it was on average 38% for WARM and 34% for STICS. This is also consistent with the above-cited studies, in which it ranged between 34% and 46%. Then, the varieties designed in this study toward the use in the near- and medium future could already be available for such adaptation, making it possible to improve future rice yields in the Mediterranean areas.

Conclusions

The variability of global rice production in a changing climate is a hot and controversial topic, and it still needs further investigation because of its prominence as a staple food in Asian top producing countries. Despite the huge number of crop modelling studies dealing with the impact of global warming on rice in tropical climates, the future trends of rice productions in Mediterranean areas is scarcely investigated and even more uncertain. Our findings indicate that the European rice sector has the potential to enhance current production levels, taking advantage of the increase of ambient CO_2 concentration and air temperature during the growing season associated with climate change conditions. The anticipation of rice sowing dates and even more the adoption of varieties with a longer crop cycle then represent effective adaptation strategies to increase rice yields and in turn farmers' income in the considered European rice areas in the short and long term.

Acknowledgements

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