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1 **Title:** Breeding implications of drought stress under future climate for upland rice in Brazil

2

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28

29 Abbreviations: TPE, target population of environments; BC, bias correction; RCP,
30 representative concentrations pathway; GCM, general circulation model; PCEW, actual to
31 potential evapotranspiration ratio.

32 **Abstract**

33 Rice is the most important food crop in the developing world. For rice production systems
34 to address the challenges of increasing demand and climate change, potential and on-farm
35 yield increases must be increased. Breeding is one of the main strategies toward such aim.
36 Here, we hypothesise that climatic and atmospheric changes for the upland rice growing
37 period in central Brazil are likely to alter environment groupings and drought stress patterns
38 by 2050, leading to changing breeding targets during the 21st century. As a result of
39 changes in drought stress frequency and intensity, we found reductions in productivity in
40 the range of 200-600 kg ha⁻¹ (up to 20 %) and reductions in yield stability throughout
41 virtually the entire upland rice growing area (except for the south-east). In the face of these
42 changes, our crop simulation analysis suggests that the current strategy of the breeding
43 program, which aims at achieving wide adaptation, should be adjusted. Based on results for
44 current and future climates, a weighted selection strategy for the three environmental
45 groups that characterise the region is suggested. For the highly favourable environment
46 (HFE, 36–41 % growing area, depending on RCP), selection should be done under both
47 stress-free and terminal stress conditions; for the favourable environment (FE, 27–40 %),
48 selection should aim at testing under reproductive and terminal stress; and for the least
49 favourable environment (LFE, 23–27 %), selection should be conducted for response to
50 reproductive stress only and for the joint occurrence of reproductive and terminal stress.
51 Even though there are differences in timing, it is noteworthy that stress levels are similar
52 across environments, with 40–60 % of crop water demand unsatisfied. Efficient crop
53 improvement targeted toward adaptive traits for drought tolerance will enhance upland rice
54 crop system resilience under climate change.

55

56 Keywords: breeding, adaptation, simulation modelling, drought stress, environment groups

57

58 **Introduction**

59 Rice is the second most important staple crop globally, contributes to ca. 15 % of daily per
60 capita calorie intake, and is the most important food crop across the developing world
61 (Cassman, 1999; Khoury *et al.*, 2014). In Latin America and the Caribbean (LAC), where
62 dependence on rice as a staple food crop is substantial, annual rice consumption ranges
63 between 6 and 57 kg person⁻¹ (Fitzgerald & Resurreccion, 2009; Kearney, 2010). Tropical
64 LAC countries, in particular, have the largest rice consumption rates (Kearney, 2010). In
65 addition to rice's current importance, global demand for rice is expected to increase as a
66 result of population growth and economic development (FAO, 2010; Tilman & Clark,
67 2014). A recent global analysis showed that rice's dietary importance across the developing
68 world has increased by 21 % in the last 30 years (Khoury *et al.*, 2014).

69
70 Particularly for rainfed rice systems, which occupy large production areas in Asia and most
71 of the production areas in Africa and Latin America (Hijmans & Serraj, 2008), concerns
72 have been raised with regard to how rice production systems will be able to sustainably
73 satisfy increasing demand in a context of stagnating potential and on-farm yield, increasing
74 yield gaps and climate change-induced yield reductions (Challinor *et al.*, 2014; Zhao *et al.*,
75 2016). More specifically, the latest IPCC report showed that, in the absence of adaptation,
76 tropical rice productivity is likely to decrease at a rate between 1.3 % and 3.5 % per degree
77 of warming (Porter *et al.*, 2014). Furthermore, increased temperatures can lead to heat
78 stress-threshold exceedance and substantially lower yield (Li *et al.*, 2015; Zhao *et al.*,
79 2016). There is thus an increasing need for better adapted cultivars combining improved
80 yield potential and lower drought sensitivity (Lafitte *et al.*, 2006).

81
82 While there may be several potential avenues to increase rice yield, crop breeding is
83 arguably one of the most promising strategies toward such aim (Dingkuhn *et al.*, 2015;
84 Ramirez-Villegas *et al.*, 2015). Higher rice productivity has been attained in irrigated
85 environments by improving yield potential while reducing crop duration, whereas less
86 success has been achieved in drought-prone environments such as upland and rainfed
87 cropping systems (Kamoshita *et al.*, 2008; Serraj & Atlin, 2008). Under climate change,
88 breeding targets may vary depending on how different abiotic stresses act during the

89 growing season, as a result of increased temperature and geographically varying
90 precipitation changes. For instance, a recent study for Australian wheat suggested shifted
91 breeding focus under future climate due to increased prevalence of heat stress during
92 flowering and a concomitant reduction in the importance of drought (Lobell *et al.*, 2015).
93 Similarly, Harrison *et al.*, (2014) reported increased frequency of severe drought stress for
94 maize in Europe. For upland rice in Brazil, where drought is a key limiting factor [30-40 %
95 probability of occurrence, with up to 30 % yield reduction, Heinemann *et al.* (2008),
96 Rabello *et al.* (2008)], a recent study by Heinemann *et al.*, (2015) suggested that breeding
97 should take account of drought stress patterns under current climate at early stages of
98 breeding to improve yield under water-limiting conditions. Shifting stress patterns and their
99 breeding implications for rice under future climate, however, are yet to be investigated.

100

101 Here, we assess changes in the prevalence and intensity of drought stress that result from
102 climate change for upland rice in central Brazil (states of Goiás, Rondônia, Mato Grosso
103 and Tocantins), the main upland rice growing area of Brazil and globally, and one of the
104 largest rainfed rice growing area in Latin America. We hypothesise that the complex
105 interplay between changing precipitation and increasing temperature during the rice
106 growing period in central Brazil (November through to January) (Collins *et al.*, 2013) and
107 growth stimulation at elevated CO₂ concentrations (Krishnan *et al.*, 2007; Kimball, 2016),
108 is likely to alter the frequency of environment groupings and drought stress patterns by
109 2050. We discuss breeding implications of these changes and suggest potential future
110 breeding directions for upland rice in Brazil.

111

112 **Materials and methods**

113 *Overview*

114 We used observed historical (1981-2005) weather from 51 weather stations in central Brazil
115 (states of Goiás, Rondônia, Mato Grosso and Tocantins, Fig. 1) and bias-corrected
116 projections (2041-2065) of an ensemble of 12 General Circulation Models (GCMs) with
117 data for the four Representative Concentrations Pathways (RCPs, 2.6, 4.5, 6.0, 8.5) to
118 simulate growth and development of upland rice. For all locations, we ran simulations with
119 the ORYZA2000 crop model for a range of management scenarios and 7 soil types

120 prevalent in the region. We employed clustering analysis on simulated yield to determine
121 environment groups, and then for each group used the same classification method on the
122 seasonal pattern of the actual-to-potential evapotranspiration ratio (PCEW) to determine the
123 main drought stress patterns. Using the historical and future clustering results we finally
124 assessed changes in the frequency of the environment groups and in the frequency and
125 intensity of the drought stress patterns. We used these results to suggest potential avenues
126 for future breeding.

127

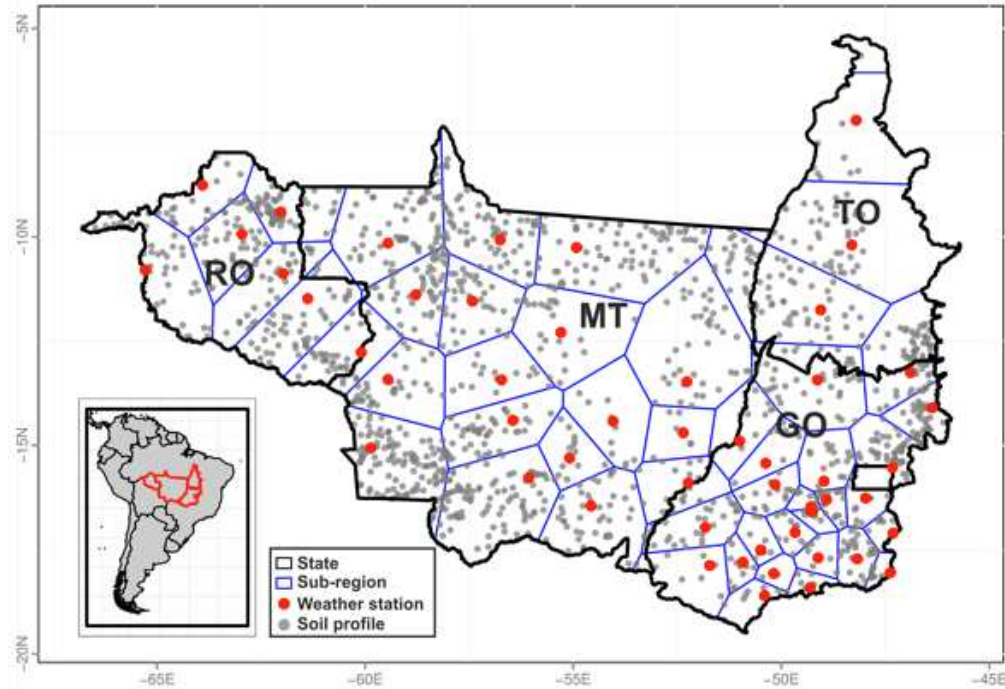
128 *Current and future weather data*

129 Observed historical 1981-2005 weather data from 51 weather stations within the study
130 region, hereafter referred to as the upland rice TPE (Target Population of Environments),
131 were gathered from a previous study (Heinemann *et al.*, 2015). Briefly, this dataset consists
132 of daily observations of temperature, precipitation and solar radiation originally gathered
133 from the Brazilian Meteorological Institute (INMET, <http://www.inmet.gov.br>), and
134 thoroughly checked for gaps and errors. For all these weather stations, except the one
135 corresponding to Santo Antônio de Goiás (49° 16' 48" S, 16° 28' 12" W, Fig. 1), daily solar
136 radiation was estimated according to Richardson & Wright (1984).

137

138 For the three stations located in the state of Tocantins, which missed data from 1981-1989,
139 were supplemented with other existing databases. More specifically, we gathered data from
140 two databases: ANA (Agência Nacional de Águas, Brazil) and the CPC (Climate Prediction
141 Center). We used ANA data to the maximum extent possible and used CPC data only for
142 filling missing ANA entries. For minimum and maximum temperature and solar radiation
143 we used the WATCH Forcing Dataset – ERA Interim (WFDEI) dataset (GPCC version)
144 (Weedon *et al.*, 2011). Following Hawkins *et al.* (2013) we `nudged` the means and
145 variability of the WFDEI data for each variable for the period 1980-1989 (10 years), based
146 on correction factors derived from the 10 years following 1989 (i.e. 1990-1999) before
147 merging it with the observed time series 1990-2005. Visual checks of the final time series
148 1981-2005 helped ensuring there were no obvious errors or implausible changes in the
149 behaviour of the time series.

150



151

152 **Figure 1** Upland rice study area in central Brazil. The area, also referred to as a Target Population
 153 of Environments (TPE), is formed by the states of Rondônia (RO), Mato Grosso (MT), Goiás (GO),
 154 and Tocantins (TO). The distribution of weather stations (red dots), their respective sub-regions
 155 (blue polygons), and the distribution of soil data used to construct the 7 soil types (light grey dots)
 156 are also shown.

157 Future climate data used here are from the CMIP5 ensemble (Taylor *et al.*, 2012) for the all
 158 four RCPs and for the four variables needed for simulating rice growth, namely, daily
 159 precipitation, solar radiation, maximum and minimum temperatures. We restricted our
 160 analyses to the 12 GCMs that presented data for all variables and RCPs (Table S1). This
 161 was preferred to using different GCMs for each RCP, or to using fewer RCPs. Since GCM
 162 data at daily scale have inherent errors, bias correction (BC) was necessary before the
 163 future data was used into the crop model (Ramirez-Villegas *et al.*, 2013). We bias-corrected
 164 the data using two different methods: (a) the delta method (DEL, hereafter), which applies a
 165 correction on the means, and (b) and the change factor method (CF, hereafter), which
 166 corrects both the means and the variability of the GCM output (Hawkins *et al.*, 2013). The
 167 use of two bias correction methods allowed quantifying uncertainty from the choice of bias
 168 correction method, an often-neglected source of uncertainty in crop modelling studies [but
 169 see Koehler *et al.*, (2013); Ramirez-Villegas and Challinor (2016)]. A combination of 12

170 [GCMs] x 4 [RCPs] x 2 [BC methods] for a total of 96 different climate scenarios for the
171 period 2041-2065 were used.

172

173 *Soil and management information*

174 We used soil data from the study of Heinemann *et al.*, (2015), who derived soil properties
175 by applying pedotransfer functions to existing field measurements (Benedetti *et al.*, 2008).

176 A total of seven soil types of differing texture were finally selected for all simulations.

177 Management information herein concerns the choice of cultivar, sowing dates, fertiliser
178 use, and maximum rooting depth, all of which are necessary inputs to the crop model. We
179 used a typical short-cycle cultivar named BRS Primavera (Primavera, hereafter), which is a
180 common check cultivar in the upland rice breeding trials and thus representative of
181 materials that breeders are currently selecting. Our choice of sowing dates is based on the
182 Brazilian Government risk zoning for the upland rice TPE (Heinemann *et al.*, 2015;
183 <http://www.agricultura.gov.br>). We sampled the entire sowing calendar (from 1st November
184 to 10th January) for upland rice at 10-day intervals (n=8), which allowed us to simulate
185 typical farmer behaviour. Since the focus of this work is to quantify the seasonal behaviour
186 of water stress and its impact, we assumed optimum nitrogen supply. Maximum rooting
187 depth was set to 50 cm, based on field observations within the study region (Heinemann *et*
188 *al.*, 2015).

189

190 *Crop model simulations*

191 To perform spatially explicit crop simulations, we divided the study area into 51 sub-areas
192 using the Thiessen polygons method (Heinemann *et al.*, 2002), based on the weather
193 stations locations (Fig. 1). For each sub-area, rice growth and development was simulated
194 with the ORYZA2000 crop model (Bouman *et al.*, 2001). ORYZA2000 is a process-based
195 simulation model developed for field-scale simulation of rice productivity that simulates
196 growth and development of rice under optimal, water-limited and nitrogen-limited
197 situations. The model integrates modules for phenology, assimilation and biomass growth,
198 leaf area dynamics, evapotranspiration, nitrogen dynamics, and soil water balance to
199 produce crop simulations at a daily time step (Li *et al.*, 2013). Here, we ran ORYZA2000
200 for rainfed conditions using the PADDY module, which is a one-dimensional water balance

201 model developed to simulate a wide range of situations. For a more comprehensive
 202 description of ORYZA2000 the reader is referred to Bouman *et al.*, (2001).

203

204 Simulation of CO₂ response was necessary under future climate. In ORYZA2000, CO₂
 205 response acts to increase both initial and maximum assimilation rates following an
 206 exponential curve with CO₂ concentrations as the independent variable [Eq. 1-2].

207

$$208 \quad CO2EFF = \frac{1 - e^{-k1CO2 * [CO2]_f - k2CO2}}{1 - e^{-k1CO2 * [CO2]_r - k2CO2}} \quad [Eq. 1]$$

209

$$210 \quad AmaxCO2 = \frac{Amax1CO2}{Amax2CO2} \left[1 - e^{\frac{-Amax3CO2 * ([CO2] - Amax4CO2)}{Amax1CO2}} \right] \quad [Eq. 2]$$

211

212 where *CO2EFF* and *AmaxCO2* are the initial and maximum rates of assimilation,
 213 respectively, [*CO2*] refers to the concentration of CO₂ in the atmosphere, with sub-indices
 214 indicating future (*f*, here defined by the mean concentration 2041-2065 for each RCP) and
 215 reference (*r*, the mean concentration during 1981-2005). The parameters *k1CO2* (Eq. 1) and
 216 *Amax3CO2* (Eq. 2) act as scaling factors to the response curve, whereas *k2CO2*=0.222 (Eq.
 217 1), *Amax1CO2*=49.57 (Eq. 2), *Amax2CO2*=34.26 (Eq. 2), and *Amax4CO2*=60 (Eq. 2) are
 218 here assumed as prescribed constants. These response curves have been derived from
 219 observed Free-Air Carbon Enrichment (FACE) and Open Top Chamber (OTC) experiments
 220 with a limited number of rice cultivars by the ORYZA2000 development team, and have
 221 been built flexible to allow simulating other cultivars with stronger or weaker CO₂
 222 fertilisation responses. ORYZA2000 thus simulates the expected response of assimilation,
 223 biomass and yield to increasing CO₂ concentrations (Kimball, 2016), although no
 224 reductions in stomatal conductance and transpiration are simulated.

225

226 Given that environment and drought stress pattern classifications and drought impact may
 227 vary depending on the extent of CO₂ response, we conducted simulations with two sets of
 228 parameters that represented the uncertainty envelope in simulated CO₂ response for rice.
 229 Specifically, we perturbed the scaling factors (*k1CO2*, *Amax3CO2*) in both response
 230 functions by increasing and decreasing their default values by 10 %. For *k1CO2*, the default

231 value was 0.00305, whereas for $A_{max3CO2}$ the default value was 0.208. Thus, our `low
232 stimulation` parameterisation used $k_{ICO2}=0.003355$ (higher than default) and
233 $A_{max3CO2}=0.1872$ (lower than default), whereas the `high stimulation` parameterisation
234 used $k_{ICO2}=0.002745$ (lower than default) and $A_{max3CO2}=0.2288$ (higher than default).
235 We chose to perturb the parameters within $\pm 10\%$ since the resulting uncertainty in
236 assimilation response to CO_2 was $\leq 20\%$, the typical range in observations of C3 crop
237 response to carbon enrichment (Long *et al.*, 2006). However, we note that this resulting
238 uncertainty is lower than multi-model ensemble uncertainty estimates of CO_2 response (Li
239 *et al.*, 2015).

240

241 All simulations were conducted for cv. Primavera using parameter values from a previous
242 study in which the model was thoroughly calibrated and evaluated for Brazilian conditions
243 (Heinemann *et al.*, 2015). In short, Heinemann *et al.*, (2015) parameterised the
244 ORYZA2000 model using data from 6 different field experiments (4 rainfed, 2 irrigated)
245 conducted at Santo Antônio de Goiás (49° 16' 48" S, 16° 28' 12" W) and evaluated the
246 model using data from 11 rainfed experiments conducted at the same location.
247 ORYZA2000 simulated phenology in the evaluation data with less than 5 days of error, and
248 yield with less than 350 kg ha⁻¹ average error for a wide range of rainfed situations (see
249 Heinemann *et al.*, 2015), and is therefore deemed appropriate for this work. Here, for both
250 historical and future climate conditions, we ran simulations for all soil (n=7) and sowing
251 dates (n=8). Historical simulations used observed weather data from each of the 51 sub-
252 regions (each containing one weather station), whereas future simulations were conducted
253 for the 96 individual future climate projections (12 GCMs x 4 RCPs x 2 BC methods) and 2
254 CO_2 parameterisations for the period 2041-2065 at each sub-region. Thus, for each of the
255 51 sub-regions we conducted 7 (soils) x 8 (sowing dates) x 12 (GCMs) x 4 (RCPs) x 2 (BC
256 methods) x 2 (CO_2 parameterisations), for a total of 10,752 future simulations per weather
257 station region, each of 25 years. This totalled ca. 13.7 million model runs for the entire
258 upland rice TPE.

259

260 *Environment and drought stress pattern classification*

261 We first determined environment groups within the upland rice TPE by clustering water-
262 and radiation-limited (i.e. attainable) yield. Clustering was performed using the entire set of
263 simulations (i.e. all planting dates, soils and sub-regions) but individually for each of the
264 climate-by-CO₂ scenarios (i.e. 1 historical, and 96 x 2 = 192 future projections). We
265 employed an agglomerative hierarchical clustering method with the Euclidean distance as
266 the dissimilarity measure and the incremental sum of squares as the fusion criterion (Ward,
267 1963). For the historical period, the number of environmental groups (clusters) was defined
268 by using the inertia gain [cf. Husson *et al.*, (2011)], the within-group sum of squares and
269 upland rice breeders knowledge of the production area. The latter was used mostly to verify
270 that areas for each environmental group coincided with anecdotal knowledge of the region.
271 For the future scenarios, the number of environmental groups determined in the historical
272 period was kept. We then determined stress patterns for each environment group. To this
273 aim, we first averaged weekly simulations of the actual-to-potential evapotranspiration ratio
274 (PCEW), which acts in ORYZA2000 to reduce photosynthesis daily, and then clustered the
275 phenological sequence patterns of PCEW using the same methods as for the environmental
276 groups. Only simulated PCEW from 21-days after sowing (mid-vegetative stage) until 2
277 weeks before physiological maturity were used as this avoided the bias that would
278 otherwise have been introduced by low PCEW values during crop establishment or during
279 senescence (Heinemann *et al.*, 2015). All clustering analyses were performed using the
280 FactoMineR package in the R statistical framework (R Core Team, 2016).

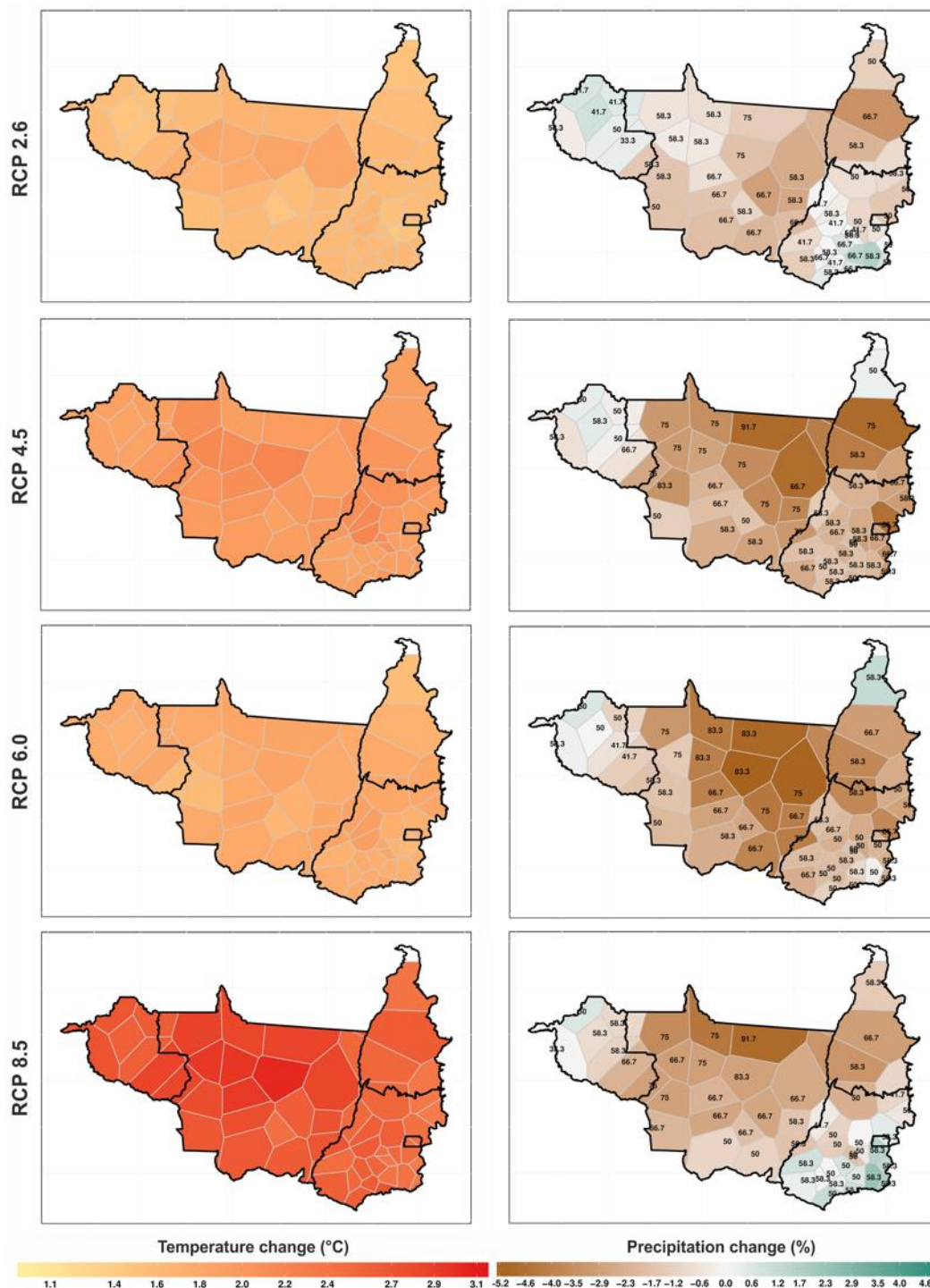
281

282 **Results**

283 *Shifted climate conditions under future climate*

284 Projected changes in precipitation and temperature are shown in Fig. 2 for all RCPs for the
285 period 2041-2065, relative to 1981-2005. Figures are specific to the rice growing period
286 (November-March). Ensemble mean temperature increases are substantial, ranging from
287 1.5 °C (minimum for RCP 2.6) to 3.1 (maximum for RCP 8.5). The largest temperature
288 increases are projected to occur in the state of Mato Grosso (MT), the largest state within
289 the TPE, whereas the least temperature increases are projected for the state of Tocantins
290 (TO, northeast). Particularly for the northern areas of the TPE, future seasonal mean
291 minimum and maximum temperatures for all RCPs are projected to be above 22 °C and 33

292 °C (respectively), both of which are critical temperature limits for rice fertility (Peng *et al.*,
 293 2004; Jagadish *et al.*, 2007).



294

295 **Figure 2** Projected changes in seasonal mean temperature (left) and seasonal total precipitation (right)
 296 across the upland rice growing region, for the period 2041-2065, relative to 1981-2005, for the rice

297 growing season (November to January). Bold numbers in the precipitation plots indicate the
298 percentage of GCM projections that agree in the direction of change.

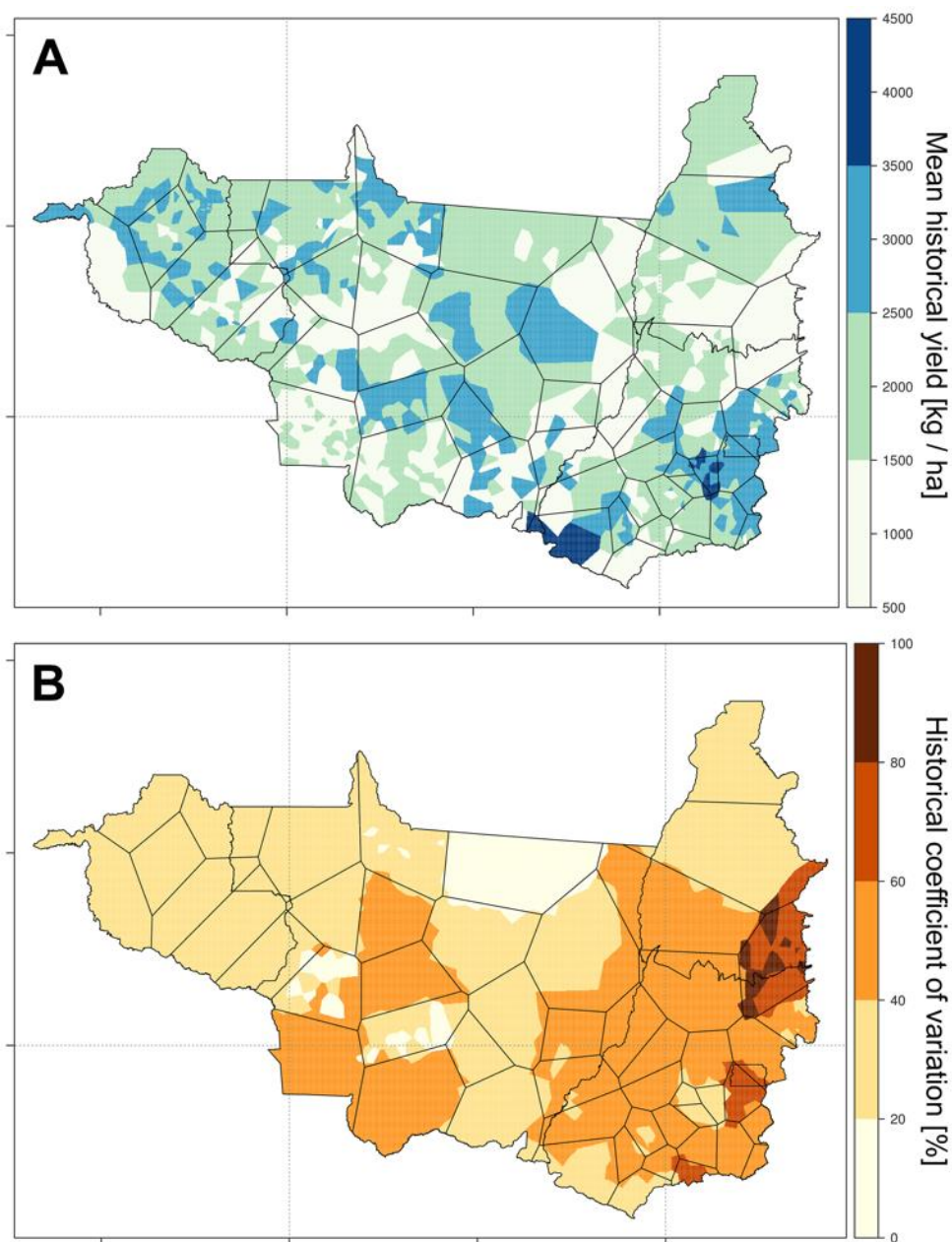
299 In contrast to temperature projections, expected precipitation changes were relatively small
300 (mean regional changes between -2 and -5 %), geographically varied, and in some areas
301 also highly uncertain (Fig. 2). Decreases in precipitation of up to 5 % are projected in the
302 state of MT for all RCPs. Particularly in the northern part of MT, precipitation projections
303 showed substantial (>70 %) agreement in the direction of the projected change. Elsewhere,
304 however, uncertainty was large, with percentage agreement rarely reaching 60 %. For TO,
305 climate change models indicated decreased precipitation. For Rondônia (RO), precipitation
306 gains were projected mostly across the north-western areas. For Goiás (GO) projected
307 precipitation changes differed across RCPs, with RCP 2.6 and RCP 8.5 showing
308 precipitation gains in the south of the state, and RCP 4.5 and RCP 6.0 showing
309 precipitation decreases across all the state. Goiás is also a state where GCM agreement is
310 low (around 50 % in most weather station regions). Thus, future global emissions and
311 climate sensitivity strongly condition future precipitation in the state.

312

313 *Yield reduction and yield stability loss induced by climate change*

314 Changes in seasonal mean temperature, total precipitation, solar radiation and CO₂
315 concentration interact to change historical mean yield and yield variability (Fig. 3). Current
316 mean yield levels are in the range 500–4,500 kg ha⁻¹. The ensemble of simulations
317 conducted here indicated that mean yield is projected to reduce across a most of the western
318 part of the upland rice TPE, and increase across the east and south-east, with some
319 differences between RCPs (Fig. 4A, B, Supplementary Fig. S1A, B). Mean yield changes
320 ranged from -600 to 600 kg ha⁻¹, with the largest reductions (400 – 600 kg ha⁻¹) projected
321 the central part of MT, followed by north-western and south-western MT (between 200 and
322 400 kg ha⁻¹). In these areas, model agreement, measured as the percentage of model
323 simulations out of the 384 simulations per soil and weather station combination (i.e. 8
324 [sowing dates] x 12 [GCMs] x 2 [BC methods] x 2 [CO₂ parameterisations]) that were in
325 the same direction of the median yield change, was generally above 60% (i.e. roughly two-
326 thirds of the model simulations) for both RCPs, and, for RCP 8.5 specifically, also above
327 80 %. Yield gains were projected across the south-eastern part of GO, as well as across

328 south-eastern and northern TO. Model agreement in these regions was, as in the areas of
329 yield decline, above 60 % and sometimes above 80 % for both RCPs. Only in specific
330 pockets within MT and RO (<10% of total area in the TPE) was model agreement close to
331 50% (no agreement, Fig. 4C, D, Supplementary Fig. S1C, D). In these areas, median
332 projected yield changes were small, likely because of uncertainty in the direction of yield
333 changes across model projections.

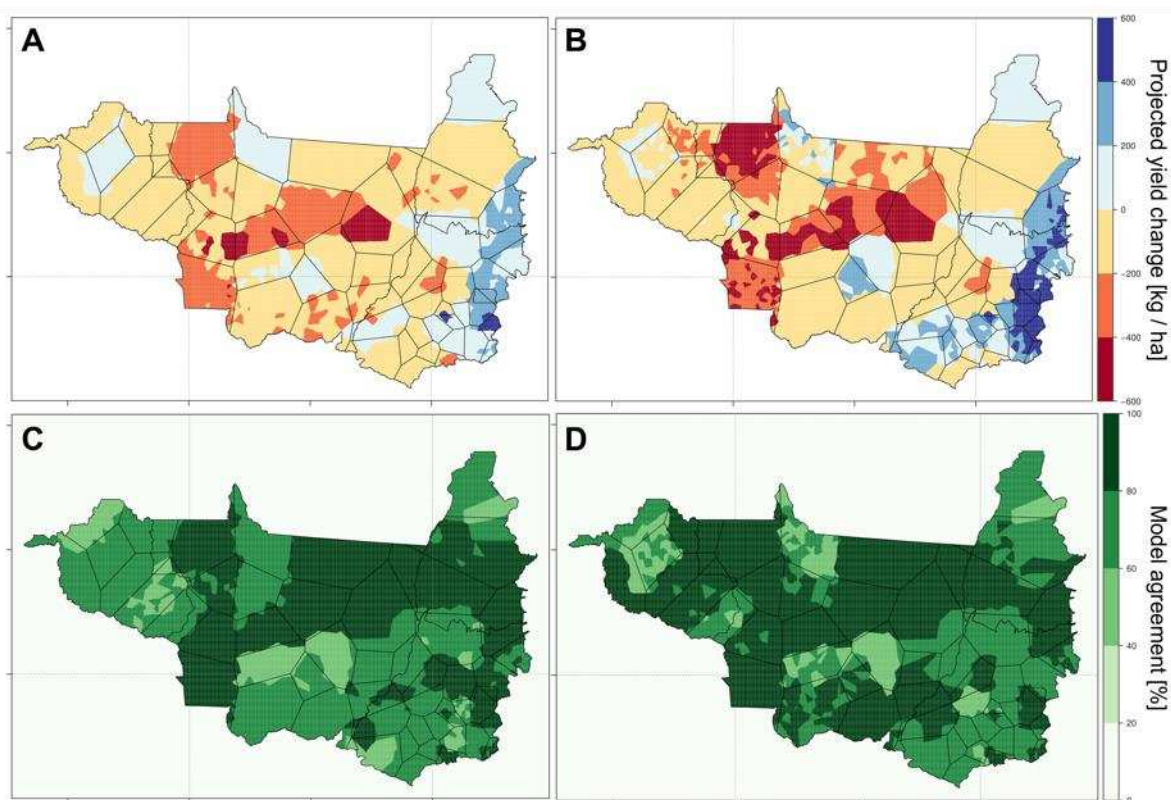


334
335 **Figure 3** Historical mean yield (A) and coefficient of variation (B), as simulated with the
336 ORYZA2000 model.

337

338 Importantly, yield stability is projected to decrease across virtually the entire TPE
339 (Supplementary Fig. S2). Projections of yield coefficient of variation indicated increases in
340 yield variability in all weather station and soil combinations within the TPE, except for
341 south-eastern GO, where decreases in yield CV are projected. For central MT, eastern TO
342 and northern RO, yield CV increases were above 10 percentage points and often above 20
343 percentage points, with high agreement (>80 %) in model projections.

344

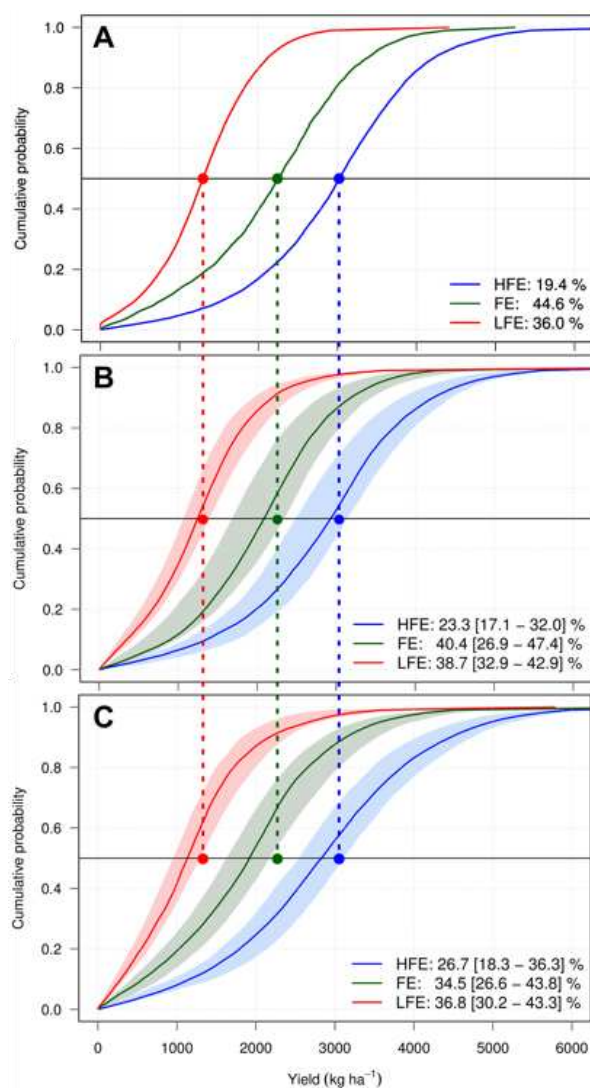


345

346 **Figure 4** Median projected change in mean yield by 2050s (A, B) and model agreement (C, D) for
347 RCP 2.6 (A, C) and RCP 8.5 (B, D) expressed as difference (in kg ha⁻¹) with respect to the historical
348 mean yield. Model agreement (C, D) is calculated as the percentage of simulations out of the 384
349 future scenario simulations (8 sowing dates x 12 GCMs x 2 BC methods x 2 CO₂ parameterisations)
350 that agree in the direction of the change with the median projected change that is shown in A and C.
351 Results for RCP 4.5 and RCP 6.0 are in Supplementary Fig. S1.

352

353 *Climate change increases the contrast between high and low yielding environments*
 354 Yield variability projections already provide some insight on the changes within growing
 355 environments in the TPE, by suggesting that climate change could enhance the contrast
 356 between the high and low yielding environments found in the historical period. In the
 357 historical period, the upland rice TPE can be divided in three environments (Fig. 5A): a
 358 highly favourable environment (HFE), a favourable environment (FE), and a least
 359 favourable environment (LFE) [also see Heinemann et al. (2015)]. These environments
 360 showed different probabilities of occurrence spatio-temporally and different median yield
 361 in the historical period: HFE is associated with a probability of 19.4 % (median yield 3,023
 362 kg ha⁻¹), FE with 44.6 % (2,184 kg ha⁻¹) and LFE with 36.0 % (1,297 kg ha⁻¹).



363

364 **Figure 5** Current and future upland rice environment groups and their associated cumulative
365 probability density function (CDF) and frequencies of occurrence in the historical period (A) and in
366 2050 for RCP 2.6 (B) and RCP 8.5 (C). Shading indicates the interquartile range of the future
367 scenario simulations. Vertical dashed lines indicate the position of the historical median relative to
368 the future climate CDFs for each environment group. The horizontal black line indicates the median
369 (50th percentile). Numbers on the bottom-right of panel (A) indicate the probability of occurrence of
370 each environment group, and for panels (B, C) they indicate the median for the RCP, with the
371 interquartile range shown in brackets. CDF plots for RCP 4.5 and RCP 6.0 are shown in
372 Supplementary Fig. S3.

373

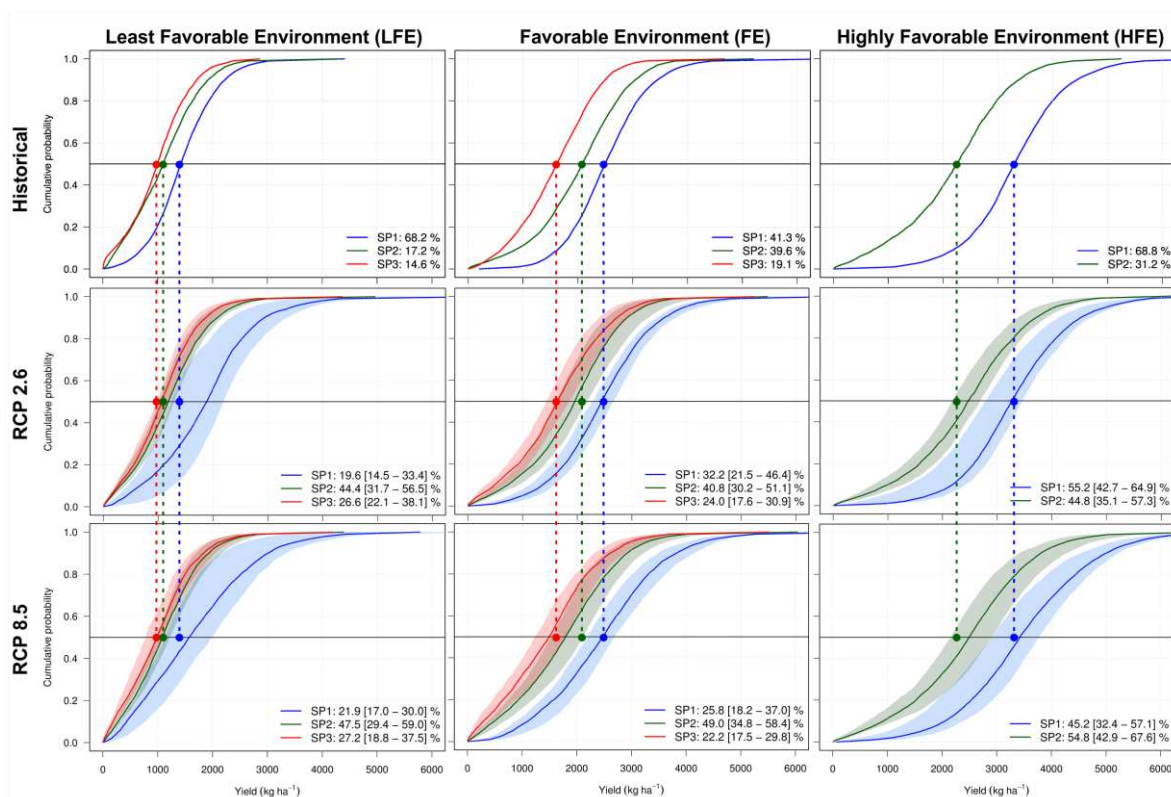
374 A more detailed analysis of environment group probabilities of occurrence and yield under
375 climate change showed reduction in the median yield for the three environments,
376 particularly under RCP 8.5 (Fig. 5B, C, Supplementary Fig. S3). However, perhaps most
377 importantly, we found a change in the probabilities of occurrence of the three environment
378 groups, with significant dependence on the RCP trajectory chosen. Results indicate that,
379 under RCP 2.6, the most likely environment remained to be FE, although with a reduction
380 in its probability of occurrence (40.4 %). For the rest of the RCPs, however, the most likely
381 environment became LFE: 36.6 % probability for RCP 4.5, 41.2 % for RCP 6.0 and 36.8
382 for RCP 8.5. At the same time, HFE also became more likely for all RCPs. In all cases,
383 these changes occurred at the expense of reducing the probability of having FE-type
384 environments, implying increased contrast between high and low yielding upland rice
385 environment groups.

386

387 *Homogenisation of drought stress within environments*

388 In setting up breeding priorities under climate change for upland rice, it is important to
389 determine not only the TPE-level environment group composition, but also the within-
390 environment-group composition of drought stress patterns. Under historical conditions,
391 three drought stress profiles were found for LFE and FE, and two for HFE. These profiles
392 are typified depending on the intensity of the drought experienced by the crop, as measured
393 by the PCEW (ratio of actual to potential evapotranspiration). Figure 6 and Supplementary
394 Fig. S4 show the yield probability distribution, whereas Figure 7 and Supplementary Fig.
395 S5 show the seasonal variation in PCEW (top rows correspond to the historical period). For

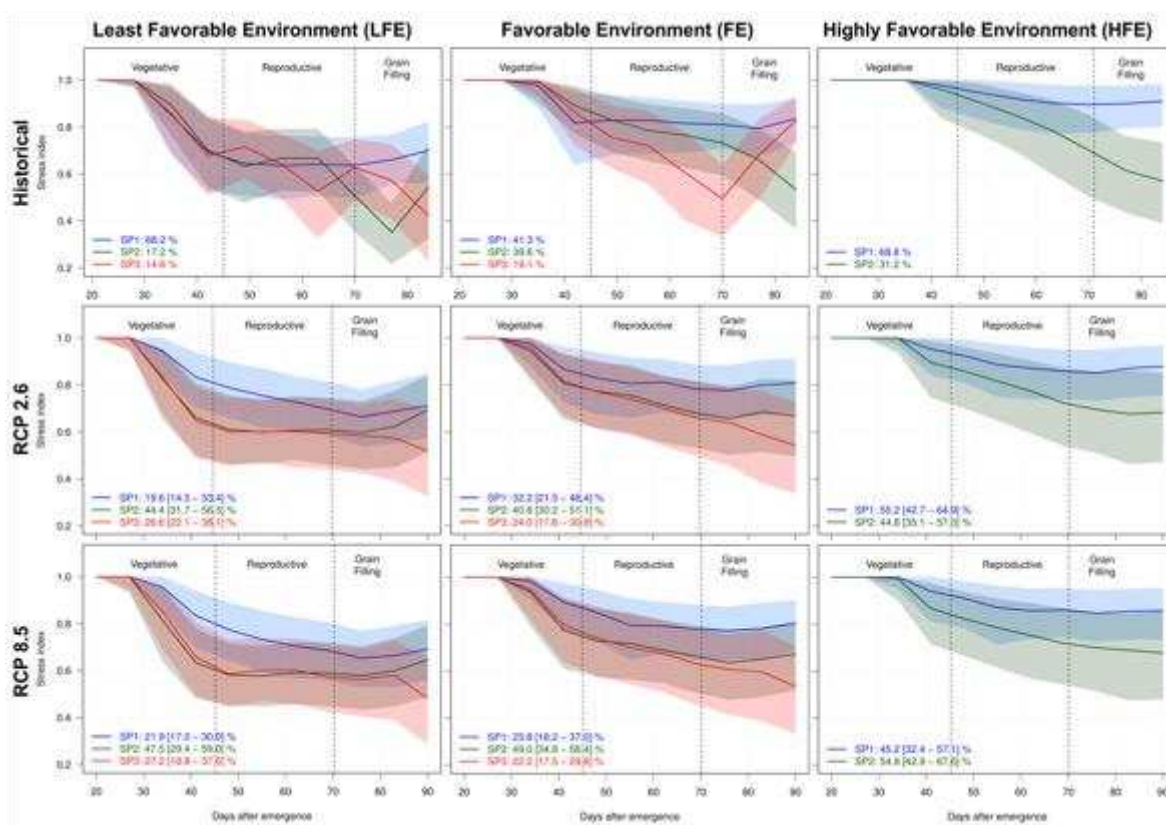
396 LFE, three stress profiles exist, namely, reproductive stress (68 % probability of
 397 occurrence, SP1), reproductive-to-grain filling stress (17 %, SP2), and terminal stress (15
 398 %, SP3). For FE, three stress profiles exist: reproductive stress (41 %, SP1), terminal stress
 399 (40 %, SP2), and severe reproductive stress (19 %, SP3); and for HFE two stress profiles
 400 were found: stress-free (69 %, SP1) and terminal stress (31 %, SP2). In general, despite
 401 differences in the timing of the stress, the intensity of drought is similar across environment
 402 groups. Stress levels, measured as percentage of unsatisfied water demand (i.e. the PCEW),
 403 were typically in the range of 40–60 %.



404
 405 **Figure 6** Cumulative probability density function (CDF) and frequencies of occurrence for upland
 406 rice stress profiles (SP) in the historical period (top row) and in 2050 for RCP 2.6 (middle row) and
 407 RCP 8.5 (bottom row) for all three environment groups: least favourable environment (LFE, left
 408 column), favourable environment (FE, middle column) and highly favourable environment (HFE,
 409 right column). Shading indicates the interquartile range of the future scenario simulations. Vertical
 410 dashed lines indicate the position of the historical median relative to the future climate CDFs for each
 411 environment group. Numbers on the bottom-right of the top row panels indicate the probability of
 412 occurrence of each profile in the environment group, and for the middle and bottom row panels they

413 indicate the median for the RCP, with the interquartile range shown in brackets. CDF plots for RCP
 414 4.5 and RCP 6.0 are shown in Supplementary Fig. S4.

415 Under climate change, we found changes in the composition of each environment group as
 416 well as in the similarity between stress patterns across environment groups. For LFE, two
 417 key differences were observed in the future scenarios with respect to the historical period.
 418 First, there was a three- and two-fold increase in the probabilities of occurrence of SP2
 419 (reproductive-to-grain filling stress) and SP3 (terminal stress), respectively, and a halving
 420 in the probability of SP1 (reproductive stress), indicating a shift in the timing of drought
 421 (Fig. 6, first column). Secondly, SP2 and SP3 became increasingly similar between them,
 422 but more distant to SP1 both regarding yield impact and in the seasonal pattern of PCEW
 423 (Fig. 6-7, first column).



424
 425 **Figure 7** Current and future upland rice stress patterns and frequencies of occurrence in the historical
 426 period (top row) and in 2050 for RCP 2.6 (middle row) and RCP 8.5 (bottom row) for all three
 427 environment groups: least favourable environment (LFE, left column), favourable environment (FE,
 428 middle column) and highly favourable environment (HFE, right column). Shading reflects the

429 interquartile range of the spatio-temporal variation of each stress profile. Numbers on the bottom-
430 right of the top row panels indicate the probability of occurrence of each profile in the environment
431 group, and for the middle and bottom row panels they indicate the median for the RCP, with the
432 interquartile range shown in brackets. Profile plots for RCP 4.5 and RCP 6.0 are shown in
433 Supplementary Fig. S5.

434 For FE, a similar behaviour was observed, whereby SP2 (terminal stress) and SP3 (severe
435 reproductive stress) both became more likely and similar. In this case, the probability of
436 occurrence of SP2 increased by roughly 20 %, whereas that of SP3 increased by roughly 15
437 % (median across the crop-climate ensemble of simulations). In both LFE and FE, SP1
438 (reproductive stress) either increases or maintains its yield levels under future climate
439 scenarios, as a result of reduced stress levels at the beginning of the reproductive period;
440 however, it becomes much less frequent than under historical conditions (ca. 70 %
441 reduction for LFE and 40 % reduction for FE for all RCPs). For HFE, we found a
442 systematic reduction in the probability of occurrence of stress-free conditions (SP1, Fig. 6-
443 7, right column) to the extent that it becomes almost as likely as the terminal stress profile
444 (SP2). At the same time, SP2 becomes less severe. The latter resulted in increased yield for
445 this stress profile.

446

447 At the environment group-level for LFE and FE, therefore, while in the historical period
448 there are three distinct drought stress profiles, results suggest that seasonal drought
449 conditions are likely to become more uniform within these environments under climate
450 change.

451

452 *Shifted growing conditions and breeding priorities for upland rice*

453 At the TPE level, the above results imply a substantial shift in growing conditions for
454 upland rice, and thus of breeding priorities. In the historical period, there was a general
455 trend for reproductive (52 % overall probability of occurrence) and terminal (29 %) stress
456 to occur separately across the entire upland rice TPE, with only 13 % of probability of
457 occurrence of stress-free conditions and 6 % probability for the crop to jointly experiencing
458 reproductive and grain-filling stress during the season. Under future climate, the probability
459 of occurrence of the joint reproductive and grain-filling stress (i.e. reproductive-to-grain-

460 filling stress) ranged between 25–28 % (depending on the RCP chosen), thus becoming the
461 most important stress after terminal stress (29–40 % overall probability). The probability of
462 reproductive stress reduced to less than half (to 17–21 %, depending on the RCP), whereas
463 the probability of stress-free conditions remained the lowest (12-13 %).

464

465 **Discussion**

466 *Implications of projected changes in mean yield and yield stability*

467 For upland rice across the savannah region in Brazil, reductions in productivity are
468 expected across most of the TPE, except for the easternmost area (see Fig. 4 and
469 Supplementary Fig. S1). Expected reductions in rice crop yield in these areas have been
470 reported by global studies. A previous global study where gridded simulations of multiple
471 crop models were used reported rice yield declines between 5–10 % by 2100 (Rosenzweig
472 *et al.*, 2014). Another study based on statistical models also reported expected yield losses
473 in the range 3–7 % by 2030 (Lobell *et al.*, 2008). On the contrary, Muller *et al.* (2015),
474 project little yield impact in Central Brazil. None of these studies, however, reported upland
475 and irrigated rice production systems separately for Brazil, or for other countries or regions,
476 none include or use the ORYZA2000 crop model, and the Lobell *et al.* (2008) study did not
477 include CO₂ response. Moreover, it is noteworthy that the study of Rosenzweig *et al.*
478 (2014) reports large uncertainty as a result of the crop model used, with models that
479 consider nitrogen stress showing large yield decreases [also see Webber *et al.* (2015)]. An
480 earlier global study where the Decision Support System for Agrotechnology Transfer
481 (DSSAT) model was used (Nelson *et al.*, 2010) to perform gridded simulations at a
482 relatively high resolution reported yield decreases between 5–25 % by 2050 in the Brazilian
483 savannah region, though that study assumed cropping systems in the savannah are irrigated.
484 Despite methodological differences, there is some agreement between existing and our
485 estimates of climate change impacts on rice crop yield for the Brazilian savannah region. In
486 addition, the substantial agreement across individual model projections in our analysis
487 suggests our results are robust.

488

489 Increase in yield variability was also projected to occur from climate change
490 (Supplementary Fig. S2). Reduction in yield stability has been reported elsewhere as a

491 major limitation for cropping systems under climate change (Challinor *et al.*, 2014; Porter
492 *et al.*, 2014). To the knowledge of the authors, however, studies specifically addressing
493 climate change impacts on yield variability in rice for Latin America or Brazil, or even
494 globally are scarce or do not exist.

495

496 The implications of high upland rice yield variability and lower mean yield are substantial
497 for both farmers, the national economy, as well as for the global food system (GFS UK,
498 2015). High yield variability and lower mean yield can cause income instability and food
499 insecurity in a region where farmers have limited access to resources and low technology
500 adoption levels (Strauss, 1991; Marcolan *et al.*, 2008). High yield variability under climate
501 change, in particular, will also increase the already high risk of cultivating upland rice,
502 which will likely accelerate the current trend towards reducing upland rice cropped areas
503 (Pinheiro *et al.*, 2006; Marcolan *et al.*, 2008; Ferreira, 2010). Urban centres in Central
504 Brazil can also be impacted due to instability in the flow of produce to the markets and in
505 market prices (Nelson *et al.*, 2010; Chen *et al.*, 2012). Deeper investigation of these
506 impacts is warranted in future studies.

507

508 The area cultivated with upland rice in Central Brazil has been in continuous decline since
509 the early 2000s (Marcolan *et al.*, 2008; Ferreira, 2010). Farmers normally prefer soybean
510 and maize, which are less sensitive to drought stress than rice and count with well-
511 established value chains in the region. The perspective of a less favourable climate only
512 makes it more difficult for upland rice to reverse the trend of declining areas. On the other
513 hand, upland rice is a good option of agronomic rotation with soybean and, in the absence
514 of drought stress, allows similar profitability. Therefore, improving the drought tolerance of
515 upland rice may be the only possibility of maintaining upland rice as a significant
516 component of agricultural systems in Central Brazil. The biological limit of adaptation of
517 this species to drought stress is still unknown.

518

519 Projected changes in crop yield and loss in yield stability will thus bring numerous
520 challenges for upland rice cropping in Brazil, highlighting the need for adaptation.

521 Adaptation strategies for cropping systems are numerous, and range from short-term coping

522 strategies through to longer-term transformations (Rippke *et al.*, 2016). Kim *et al.* (2013),
523 for temperate rice, found that cultivar and planting date adaptation can counteract negative
524 climate change impacts. For Central Brazil, Heinemann *et al.* (2015) suggest early planting
525 dates can increase yield. Moreover, efficient breeding and delivery systems are needed
526 under future climate so as to deliver novel varieties that are adapted to and respond well
527 under the specific drought conditions found here (Silva *et al.*, 2009; Breseghello *et al.*,
528 2011; Challinor *et al.*, 2016).

529

530 *Breeding implications of changes in environment groups and stress profiles*

531 The current upland rice breeding strategy in Embrapa is composed of two separate breeding
532 programs: (i) the conventional breeding program, focusing on increasing grain yield,
533 stability and adaptability to the undivided TPE; and (ii) a drought tolerance breeding
534 program created in 2004. The conventional breeding program uses two main breeding
535 methods: modified pedigree and recurrent selection. In both methods, the first three
536 generations are conducted in a single location under good environmental conditions (Santo
537 Antonio de Goiás, GO). The fourth generation genotypes ($F_{2:4}$ or $S_{0:2}$) are tested in multi-
538 location trials of at least 5 sites. This implies in exposing the progenies to different local
539 weather conditions, including drought stress. The best progenies, based on the results of
540 these trials' joint statistical analysis, are selected for single plant selection (modified
541 pedigree) or recombination (recurrent selection). With time, the upland rice breeding
542 program is improving its genetic stability while exploiting the GxE interactions through
543 seeking wide adaptability. The same philosophy is applied from generation F_6 to F_{10} of the
544 pedigree method, as the homozygosity gets higher, the number of lines declines, tested in a
545 growing number of sites. The network must represent the TPE, including the stresses that
546 occur routinely (Heinemann *et al.*, 2015). With the modified pedigree methodology and a
547 very broad network represented by the multi-location trials (around 40 trials with F_{10} elite
548 lines in the upland rice production area in Brazil), it is possible to evaluate and select lines
549 with high stability in a wide range of environments. This strategy aims to select high
550 yielding elite lines with the capacity to respond favourably to changes in the environment
551 (i.e. with wide adaptation) and at the same time to have a highly predictable performance in
552 different environmental conditions (Colombari Filho *et al.*, 2013). Currently, the modified

553 pedigree method achieves a yield gain of 2.66 % per cycle (Martinez *et al.*, 2014), but it has
554 a tendency to reduce drought tolerance (Pinheiro *et al.*, 2006; Silveira *et al.*, 2015).

555

556 A drought tolerance breeding program was created in 2004. In such program, the strategy is
557 to select genotypes with high yield potential under optimal conditions that are able to
558 maintain good productivity under drought. This program is conducted in the drought
559 phenotyping site of Porangatu, state of Goiás, Brazil (Martinez *et al.*, 2014). The program
560 started in 2004 with the identification of drought tolerant donors and the cross of those with
561 lines or varieties with a minimum level of drought tolerance. Nowadays, the progenies are
562 in F_{2:4} generations, and the first releases are expected to occur within the next 10 years. All
563 generations are subjected to SP1 and SP2 drought stress patterns.

564

565 Under current climate, we found that unstressed conditions occur roughly 13 % of the time,
566 whereas under future climate we find that this probability of occurrence either remains
567 unchanged or reduces for all RCPs (12 % in RCP 8.5 to 13 % in RCP 2.6). The existing
568 breeding strategy results in high-yielding cultivars with a medium tolerance under stressful
569 conditions, and therefore still leave risks to farmers that adopt such varieties. It enhances
570 wide adaptation and has led to improved genotypic stability, but selection weights equally
571 all stresses, and there is no consideration of environmental co-variables (e.g. weather, soil
572 water contents) in the statistical analysis. Due to the diversity of stresses found, a revised
573 breeding strategy is suggested for upland rice in Brazil both under current and future
574 climate.

575

576 The results shown in this work will improve the breeding program to deal with climate
577 changes aiming to deliver cultivars adapted to the new TPE. Foremost, the early evaluation
578 should be done in sites of the multi-location network chosen based on our clustering
579 analysis of historical and future yield (also see Heinemann *et al.* 2015), in which the upland
580 area is classified in HFE, FE and LFE. Combining that with the weather data evaluation
581 from each site, will make a detailed weighted selection possible. A better process of
582 selection will help breeders to select the desired progenies, lines, cultivars adapted to the
583 future. Another improvement in the breeding program could be the modification in the

584 drought stress protocol normally used in drought phenotyping site of Porangatu to apply the
585 same type of stress predicted for 2050.

586

587 Under current climate, a differentiated strategy that isolates drought stress profiles is
588 recommended, since this would allow to control for GxE interactions (Heinemann *et al.*,
589 2015, 2016). The best strategy under current conditions would be: for HFE, specific
590 adaptation to stress-free conditions (i.e. selection for yield potential); for FE, wide
591 adaptation to drought, or selection for yield under drought, weighted by the probability of
592 different drought profile conditions; and for LFE, specific adaptation to reproductive
593 drought stress, or a weighted selection strategy as in FE.

594

595 Results presented here indicated that the selection strategy can be adjusted. For HFE, a
596 weighted selection strategy whereby genotypes are tested both under stress-free and
597 terminal stress conditions may be needed, since these two stress profiles each have ~50 %
598 probability of occurrence. For FE, selection should aim at testing under reproductive
599 (probability of occurrence 62–70 %) and terminal stress (ca. 30–38 %) and then weighting
600 genotype performance according to these probabilities. For LFE, breeders could also adopt
601 a weighted selection strategy, but trials should be conducted for response to reproductive
602 stress (20–25 % probability) and for the joint occurrence of reproductive and terminal stress
603 (75–80 %). As demonstrated by previous studies (though on a different cereal crop),
604 weighted selection can help isolating the environmental components of observed drought
605 impacts from the genotypic component, thus allowing for quicker breeding gains under
606 stressful environments (Chenu *et al.*, 2011). Stress levels were similar across environments,
607 with the percentage of unsatisfied water demand being typically in the range of 40–60 %.

608

609 It is noteworthy that we have focused only on one genotype (Primavera), whereas
610 environment groups and stress patterns may depend on the type of cultivars grown by the
611 farmers (i.e. GxE interaction). While Primavera is currently used as a check cultivar in the
612 conventional breeding program and is hence representative of genotypes released to the
613 public, clearly, as a result of the breeding process at Embrapa, changes have occurred and
614 will continue to occur in the characteristics of the germplasm released and grown by

615 farmers in the last 30-40 years, leading to changes in the environments and stress patterns.
616 In particular, during 1980s and 1990s a major shift from releasing landraces (e.g. cv.
617 Douradão) to releasing modern cultivars (e.g. cv. Primavera) occurred in the breeding
618 program, whereas in late 1990s wide hybridizations were carried out, introducing *indica*
619 genes into a predominant *japonica* background with significant increase of yield potential
620 especially under highly favorable conditions (Martinez *et al.*, 2014). These activities have
621 resulted in cultivars with longer growing cycle, and lower root length density, but generally
622 less drought tolerance (Pinheiro *et al.*, 2006; Breseghello *et al.*, 2011). In fact, cv.
623 Primavera has been reported to be more drought sensitive than its predecessors (Pinheiro *et*
624 *al.*, 2006; Heinemann *et al.*, 2011; Silveira *et al.*, 2015). Further changes will likely
625 continue to occur as upland rice breeding continues in Brazil, especially as genotypes
626 developed by the drought-tolerant breeding program created in 2004 are released and
627 adopted. Therefore, while we argue that the current production situation in central Brazil is
628 well represented by cv. Primavera, continuous updating of environmental groups and stress
629 patterns will be required in the next decades. Future studies that include a wider variety of
630 varieties, with different levels of drought tolerance and different growing cycles can help in
631 analysing the genotypic dependencies of the environmental and stress types identified here.
632 These will further help the breeding program in designing selection trials and defining the
633 selection strategy.

634

635 The costs of conducting breeding and selection trials for a wide range of drought conditions
636 to be able to weight genotype selection across the entire TPE could, however, constrain its
637 applicability. This is particularly true for publicly funded breeding programs. In such
638 situations, a viable option for each environment type or even for the undivided TPE would
639 be to develop genotypes with wide adaptation to drought. Drought tolerance in upland rice
640 can be achieved by selecting for high grain yield in stress environments, or by using
641 marker-assisted selection on less complex traits (Bernier *et al.*, 2008). An example of this
642 strategy comes from the upland rice in Brazil. The last variety released, BRS Esmeralda, is
643 the first variety from Embrapa's breeding program with drought tolerance. BRS Esmeralda
644 was directly selected under a variety of weather conditions, including drought stress. Its
645 high stability is shown by Colombari (Colombari Filho *et al.*, 2013). Additionally, success

646 in other publicly-funded breeding programs such as those of maize in Africa and common
647 beans in Central America and Africa provides evidence of the potential for breeding
648 drought-tolerant materials for adaptation to climate variability and change (Beebe *et al.*,
649 2011; Cairns *et al.*, 2013).

650

651 Identifying the key physio-morphological traits that confer drought tolerance is also critical
652 for the efficient selection of genetic material in breeding trials. Although more research will
653 be required for a complete understanding of which traits are desirable for a specific
654 environment and drought pattern, existing research suggests that improved root
655 characteristics, shorter cycles (i.e. drought escape), osmotic adjustment, as well as quicker
656 and larger assimilate translocation from stems to panicles would likely be desirable traits to
657 improve drought responses (Fukai & Cooper, 1995; Dingkuhn *et al.*, 2015).

658

659 *Uncertainty and decision making in breeding programs*

660 Model projections of climate change impacts can help guide decisions on adaptation
661 (Ranger & Garbett-Shiels, 2011), and, in this case, help establishing clear targets for the
662 upland rice breeding program in Brazil. Large uncertainty in model projections, however,
663 can preclude these decisions (Vermeulen *et al.*, 2013). Hence, further to what has been
664 discussed above on the representativeness of cv. Primavera, limitations arise in our
665 analysis, most notably, because future climate projections are inherently uncertain, and
666 because, as in any model-based analysis, the crop model used does not capture crop
667 response perfectly (e.g. limitations in simulating CO₂ response, heat stress, or site-specific
668 farmer management). Here, we accounted for a range of uncertainty sources, namely,
669 emissions pathways (RCPs), simulated climate sensitivity (using multiple GCMs), bias
670 correction methods, and rice crop response to enhanced CO₂ concentrations. Importantly,
671 our study is one of the first crop simulation studies that explicitly quantifies the response of
672 the crop CO₂ concentrations and of different bias correction methods [also see Ramirez-
673 Villegas and Challinor (2016)]. Agreement across model projections of yield and yield
674 stability was found throughout most of the upland rice TPE (see Fig. 4C, D). Also, despite
675 variability across crop-climate model projections for environment-specific yield
676 distributions and drought profiles, differences between the medians were substantial, and

677 overlaps between uncertainty bounds were small, indicating our results are robust towards
678 modelling uncertainties (Fig. 5-6). Recent studies have also shown that predictability can be
679 achieved for certain crop processes (Challinor *et al.*, 2016), at long timescales (Rippke *et*
680 *al.*, 2016), or for certain model outcomes [e.g. adaptation vs. no adaptation, Ramirez-
681 Villegas and Challinor (2016); Porter *et al.* (2014)]. The latter studies are particularly
682 relevant to our analysis, since they specifically emphasise that while uncertainty is
683 prevalent in model projections of crop yield, there is robustness as to the direction and
684 impact of adaptation strategies. Nevertheless, we argue that, despite the uncertainties and
685 limitations, the benefits of breeding drought-tolerant upland rice will be substantial during
686 the 21st century. If the current level of drought tolerance is not improved, upland rice may
687 be replaced by other, more drought tolerant, cash crops.

688

689 **Conclusions**

690 In this study, we assessed changes in the prevalence and intensity of drought stress due to
691 climate change for upland rice in central Brazil, with a view on the implications that these
692 changes have on the current breeding strategy for upland rice in Brazil. In the face of
693 climate change-induced decreases in mean yield and losses in yield stability, our results
694 suggest that the current strategy of the breeding program can be improved to minimize the
695 impact of drought stress on new cultivars.

696

697 Under climate change scenarios, based on our results and on those of a previous study that
698 focused on historical climates (Heinemann *et al.*, 2015), we recommend a weighted
699 selection strategy for all the environment groups in the TPE. Although only economic *ex-*
700 *ante* and/or *ex-post* technology impact assessments will allow determining whether it is
701 economically feasible to change the current breeding strategy to be modified, it is necessary
702 to consider future projected climatic conditions in the breeding pipeline. Improving the
703 adaptive traits of germplasm to respond better under drought stress will ultimately facilitate
704 upland rice systems adaptation to climate change, improving food security and farmer
705 livelihoods.

706

707 There are a variety of future research avenues that could be pursued based on the results
708 presented here. Although the ORYZA2000 model already simulates heat stress, future
709 studies could use available and/or new experimental data to evaluate heat stress response in
710 the model, and then use it to quantify the occurrence of heat-stressed environments. Heat
711 has been reported as being of major importance for rice globally (Teixeira *et al.*, 2013; van
712 Oort *et al.*, 2015), and specifically also for the southern part of the upland rice TPE studied
713 here (Teixeira *et al.*, 2013). Future work could also involve the validation of the growing
714 environments reported here with field trials, and the determination of potential parents and
715 physio-morphological traits that are key for drought tolerance. Finally, clearly, the drought
716 stress profiles and yield environments that we find can change as new cultivars become
717 available and adopted, and future analyses will be required to determine if the breeding
718 strategy is indeed on track, and yield progress is being made under the different drought
719 types that exist in the target region.

720

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735

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936

937 **Figure captions**

938

939 **Figure 1** Upland rice study area in central Brazil. The area, also referred to as a Target
940 Population of Environments (TPE), is formed by the states of Rondônia (RO), Mato Grosso
941 (MT), Goiás (GO), and Tocantins (TO). The distribution of weather stations (red dots),
942 their respective sub-regions (blue polygons), and the distribution of soil data used to
943 construct the soil scenarios (light grey dots) are also shown.

944

945 **Figure 2** Projected changes in seasonal mean temperature (left) and seasonal total
946 precipitation (right) across the upland rice growing region, for the period 2041-2065, relative
947 to 1981-2005, for the rice growing season (November to January). Bold numbers in the
948 precipitation plots indicate the percentage of GCM projections that agree in the direction of
949 change.

950

951 **Figure 3** Historical mean yield (A) and coefficient of variation (B), as simulated with the
952 ORYZA2000 model.

953

954 **Figure 4** Median projected change in mean yield by 2050s (A, B) and model agreement (C,
955 D) for RCP 2.6 (A, C) and RCP 8.5 (B, D) expressed as difference (in kg ha^{-1}) with respect
956 to the historical mean yield. Model agreement (C, D) is calculated as the percentage of
957 simulations out of the 384 future scenario simulations (8 sowing dates x 12 GCMs x 2 BC
958 methods x 2 CO_2 parameterisations) that agree in the direction of the change with the median
959 projected change that is shown in A and C. Results for RCP 4.5 and RCP 6.0 are in
960 Supplementary Fig. S1.

961

962 **Figure 5** Current and future upland rice environment groups and their associated cumulative
963 probability density function (CDF) and frequencies of occurrence in the historical period (A)
964 and in 2050 for RCP 2.6 (B) and RCP 8.5 (C). Shading indicates the interquartile range of
965 the future scenario simulations. Vertical dashed lines indicate the position of the historical
966 median relative to the future climate CDFs for each environment group. The horizontal black
967 line indicates the median (50th percentile). Numbers on the bottom-right of panel (A) indicate

968 the probability of occurrence of each environment group, and for panels (B, C) they indicate
969 the median for the RCP, with the interquartile range shown in brackets. CDF plots for RCP
970 4.5 and RCP 6.0 are shown in Supplementary Fig. S3.

971

972 **Figure 6** Cumulative probability density function (CDF) and frequencies of occurrence for
973 upland rice stress profiles (SP) in the historical period (top row) and in 2050 for RCP 2.6
974 (middle row) and RCP 8.5 (bottom row) for all three environment groups: least favourable
975 environment (LFE, left column), favourable environment (FE, middle column) and highly
976 favourable environment (HFE, right column). Shading indicates the interquartile range of the
977 future scenario simulations. Vertical dashed lines indicate the position of the historical
978 median relative to the future climate CDFs for each environment group. Numbers on the
979 bottom-right of the top row panels indicate the probability of occurrence of each profile in
980 the environment group, and for the middle and bottom row panels they indicate the median
981 for the RCP, with the interquartile range shown in brackets. CDF plots for RCP 4.5 and RCP
982 6.0 are shown in Supplementary Fig. S4.

983

984 **Figure 7** Current and future upland rice stress patterns and frequencies of occurrence in the
985 historical period (top row) and in 2050 for RCP 2.6 (middle row) and RCP 8.5 (bottom row)
986 for all three environment groups: least favourable environment (LFE, left column),
987 favourable environment (FE, middle column) and highly favourable environment (HFE, right
988 column). Shading reflects the interquartile range of the spatio-temporal variation of each
989 stress profile. Numbers on the bottom-right of the top row panels indicate the probability of
990 occurrence of each profile in the environment group, and for the middle and bottom row
991 panels they indicate the median for the RCP, with the interquartile range shown in brackets.
992 Profile plots for RCP 4.5 and RCP 6.0 are shown in Supplementary Fig. S5.

993