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1

2 DR. GATIEN NOËL FALCONNIER (Orcid ID : 0000-0003-3291-650X)

3 DR. MYRIAM ADAM (Orcid ID : 0000-0002-8873-6762)

4 DR. BRUNO BASSO (Orcid ID : 0000-0003-2090-4616)

5 DR. ELIZABETH MEIER (Orcid ID : 0000-0003-2394-8120)

6 MR. TESFAYE SHIFERAW SIDA (Orcid ID : 0000-0001-6482-2669)

7 DR. F TAO (Orcid ID : 0000-0001-8574-0080)

8 DR. HEIDI WEBBER (Orcid ID : 0000-0001-8301-5424)

9

10

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14 **Modelling climate change impacts on maize yields under low nitrogen input conditions**
15 **in sub-Saharan Africa**

16

17 GN Falconnier^{*1}, M Corbeels^{1,2}, KJ Boote³, F Affholder¹, M Adam^{4,5}, DS MacCarthy⁶, AC
18 Ruane⁷, C Nendel⁸, AM Whitbread⁹, E Justes¹⁰, LR Ahuja¹¹, F.M. Akinseye¹², IN Alou¹³,
19 KA Amouzou¹⁴, S.S. Anapalli¹⁵, C Baron^{16,17}, B Basso¹⁸, F Baudron¹⁹, P Bertuzzi²⁰, AJ
20 Challinor²¹, Y Chen^{22,23}, D Deryng^{24,40}, ML Elsayed²⁵, B Faye²⁶, T Gaiser²⁶, M Galdos²¹, S
21 Gayler²⁷, E Gerardeaux¹, M Giner¹, B Grant²⁸, G Hoogenboom³, ES Ibrahim⁸, B Kamali⁸, KC
22 Kersebaum⁸, SH Kim²⁹, M van der Laan¹³, L Leroux^{1,30}, JI Lizaso³¹, B Maestrini¹⁸, EA
23 Meier³², F Mequanint²⁷, A Ndoli¹⁹, CH Porter³, E Priesack³³, D Ripoche²⁰, T Sida³⁴, U
24 Singh³⁵, W Smith²⁸, A Srivastava²⁶, S Sinha²¹, F Tao^{22, 23, 36}, PJ Thorburn³², D Timlin³⁷, B
25 Traore³⁸, T Twine³⁹, H Webber⁸

26 ¹AIDA, Univ Montpellier, CIRAD, Montpellier, France, ²CIMMYT, Nairobi, Kenya, ³University of Florida, Gainesville, FL, 32611-0570,

27 USA, ⁴CIRAD, UMR AGAP, Bobo-Dioulasso 01, Burkina Faso, ⁵AGAP, Univ Montpellier, CIRAD, INRA, Montpellier SupAgro,

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28 Montpellier, France, ⁶ Soil and Irrigation Research Centre, School of Agriculture, College of Basic and Applied Science, University of
29 Ghana, Accra, Ghana, ⁷Climate Impacts Group, National Aeronautics and Space Administration Goddard Institute for Space Studies, 2880
30 Broadway, New York, NY 10025, USA, ⁸Leibniz Centre for Agricultural Landscape Research, Müncheberg, Germany, ⁹International Crops
31 Research Institute for the Semi-Arid Tropics (ICRISAT), Patancheru, India, ¹⁰PERSYST, Univ Montpellier, CIRAD, Montpellier, France,
32 ¹¹USDA-ARS, Fort Collins, CO, USA, Retired, ¹²International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Kano,
33 Nigeria, ¹³Department of Plant and Soil Sciences, University of Pretoria, Private Bag X20 Hatfield, 0028 South Africa, ¹⁴African Plant
34 Nutrition Institute (APNI), West Africa Program, P.O.Box 1576, Yamoussoukro, Cote d'Ivoire, ¹⁵USDA-ARS, Sustainable Water
35 Management Research Unit, P.O. Box 350, Stoneville, MS 38776, United States, ¹⁶CIRAD, UMR TETIS, F-34398 Montpellier, France,
36 ¹⁷TETIS, Univ Montpellier, AgroParisTech, CIRAD, CNRS, IRSTEA, Montpellier, France, ¹⁸Department of Earth and Environmental
37 Sciences, Michigan State University, East Lansing, MI, 48824, USA, ¹⁹CIMMYT, Harare, Zimbabwe, ²⁰INRA, Agroclim, France, ²¹Institute
38 for Climate and Atmospheric Science, School of Earth and Environment, University of Leeds, Leeds LS2 9JT, UK ²²Key Laboratory of Land
39 Surface Pattern and Simulation, Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing
40 100101, China, ²³College of Resources and Environment, University of Chinese Academy of Sciences, Beijing 100049, China, ²⁴Integrative
41 Research Institute on Transformations of Human-Environment Systems (IRI THESys), Humboldt-Universität zu Berlin, 10099, Berlin,
42 Germany, ²⁵MALR-ARC, Central Laboratory for Agricultural Climate (CLAC), Giza, Egypt, ²⁶Crop Science Group, Institute of Crop
43 Science and Resource Conservation (INRES), University of Bonn, Bonn, Germany, ²⁷Institute of Soil Science and Land Evaluation,
44 Biogeophysics, University of Hohenheim, Stuttgart, Germany, ²⁸Ottawa Research and Development Centre, Agriculture and Agri-Food
45 Canada, Ottawa, ON, Canada, ²⁹University of Washington, School of Environmental and Forest Sciences, Seattle, United States, ³⁰CIRAD,
46 UPR AIDA, Dakar, Senegal, ³¹CEIGRAM- Universidad Politécnica de Madrid, ETSIAAB, Madrid, Spain, ³²CSIRO Agriculture and Food,
47 Queensland Bioscience Precinct, St Lucia, Qld 4067, Australia, ³³Institute of Biochemical Plant Pathology, Helmholtz Center Munich,
48 Neuherberg, Germany, ³⁴CIMMYT, Addis Ababa, Ethiopia, ³⁵International Center for Soil Fertility and Agricultural Development, Muscle
49 Shoals, AL 35662, United States, ³⁶Natural Resources Institute Finland (Luke), Helsinki, Finland, ³⁷Crop Systems and Global Change
50 Research Unit, USDA-ARS, Beltsville, MD, United States, ³⁸IER, Bamako, Mali, ³⁹University of Minnesota, Department of Soil, Water, and
51 Climate, St. Paul, MN 55108, United States, ⁴⁰NewClimate Institute, Berlin, Germany

52

53 *gatie.falconnier@cirad.fr

54

55 Abstract

56 Smallholder farmers in sub-Saharan Africa (SSA) currently grow rainfed maize with limited
57 inputs including fertilizer. Climate change may exacerbate current production constraints.
58 Crop models can help quantify the potential impact of climate change on maize yields, but a
59 comprehensive multi-model assessment of simulation accuracy and uncertainty in these low-
60 input systems is currently lacking. We evaluated the impact of varying [CO₂], temperature
61 and rainfall conditions on maize yield, for different nitrogen (N) inputs (0, 80, 160 kg N ha⁻¹)
62 for five environments in SSA, including cool sub-humid Ethiopia, cool semi-arid Rwanda, hot
63 sub-humid Ghana and hot semi-arid Mali and Benin using an ensemble of 25 maize models.
64 Models were calibrated with measured grain yield, plant biomass, plant N, leaf area index,
65 harvest index and in-season soil water content from two-year experiments in each country to
66 assess their ability to simulate observed yield. Simulated responses to climate change factors
67 were explored and compared between models. Calibrated models reproduced measured grain
68 yield variations well with average rRMSE of 26%, although uncertainty in model prediction

69 was substantial (CV = 28%). Model ensembles gave greater accuracy than any model taken at
70 random. Nitrogen fertilization controlled the response to variations in [CO₂], temperature and
71 rainfall. Without N fertilizer input, maize (i) benefited less from an increase in atmospheric
72 [CO₂], (ii) was less affected by higher temperature or decreasing rainfall and (iii) was more
73 affected by increased rainfall because N leaching was more critical. The model inter-
74 comparison revealed that simulation of daily soil N supply and N leaching plays a crucial role
75 in simulating climate change impacts for low-input systems. Climate change and N input
76 interactions have strong implications for the design of robust adaptation practices across SSA,
77 because the impact of climate change will be modified if farmers intensify maize production
78 with more mineral fertilizer.

79 *Keywords: crop simulation model, model intercomparison, ensemble modelling, uncertainty,*
80 *smallholder farming systems.*

81

82 **1. Introduction**

83 Rainfed maize production is crucial for food security and smallholder livelihoods in sub-
84 Saharan Africa (SSA). Maize is the largest contributor to the total value of staple crop
85 production in Western, Eastern, Central and Southern Africa (OCDE, FAO, 2016). With
86 limited access to means of income diversification and safety nets, smallholder farmers in SSA
87 are highly vulnerable to climate change (Connolly-Boutin and Smit, 2016; Descheemaeker et
88 al., 2016). Temperatures are expected to increase in West, East and Southern Africa, with
89 multi-model climate projections indicating a warming of 1 to 4°C in the decades of 2081–
90 2100 relative to 1986–2005 depending on the Representative Concentration Pathway (RCP)
91 considered (IPCC, 2013). Annual rainfall is expected to increase in West and East Africa (0 to
92 +12% depending on RCP) and to decrease in Southern Africa (-5 to -10% depending on RCP)
93 (IPCC, 2013). The impact of climate change on maize productivity across SSA is uncertain,
94 but significant losses are expected, especially in Southern Africa (Conway et al., 2015; Lobell
95 et al., 2008; Rosenzweig et al., 2014) and West Africa (Sultan and Gaetani, 2016).
96 Smallholder farms in SSA usually obtain low maize yields, on average 1.8 t ha⁻¹ in 2017
97 (FAOSTAT, 2018). These low yield levels are largely attributable to low fertilizer use, which
98 averaged 12, 2 and 3 kg ha⁻¹ for N, P and K respectively (FAOSTAT, 2018). With limited
99 irrigation and inadequate access and use of nutrient inputs, water and nitrogen (N) stresses
100 prevail (Folberth et al., 2013).

101 Process-based soil-crop models can help quantify the potential impact of climate change on
102 maize productivity in smallholder context whilst accounting for the water and N (and/or other
103 plant nutrient) stresses (*e.g.* Kihara et al., 2012). Soil-crop models simulate biophysical
104 processes resulting from plant genetics, crop management, soil properties, and weather, thus
105 tracking water, carbon, N, (phosphorous (P) to some extent) dynamics, and energy balances as
106 plants develop through the different phenological growth phases. As such, models must
107 consider a range of complex processes and their interactions with weather, soil, and crop
108 management, *e.g.* the effect of soil water dynamics on nutrient supply and uptake, or the
109 influence of soil organic matter and organic amendments on nutrient availability during the
110 growing season. The consideration of these soil- and climate-related processes increases
111 model complexity, number of model parameters and data demand for model calibration.
112 Compared to simulating irrigated systems with high nutrient inputs, where water and N are
113 less often limiting factors, the simulation of rainfed, low-input cropping systems requires
114 more detailed model parameterization, especially of the soil processes. Model parameters
115 related to soil water and nutrient processes are critical for the simulation of low input systems
116 (Corbeels et al., 2016; Jones et al., 2012). Main soil processes to be taken into account are: i)
117 soil water dynamics, including infiltration from rainfall, redistribution within the soil profile
118 and evapotranspiration, (ii) decomposition of soil organic matter and associated
119 mineralization of N, and (iii) N leaching below the root zone. Accurate simulation of the plant
120 available water is crucial for simulation of crop water stress (Whitbread et al. 2017), while
121 mineralization and leaching largely determine soil N availability for plant uptake and
122 therefore regulate N stress on crop growth. Hence, greater uncertainty related to model
123 processes and parameterization is expected in the responses of low-input cropping systems to
124 climate change. For example, it is known that N stress can strongly impact crop responses to
125 variation in [CO₂], temperature and rainfall (Affholder, 1995; Ziska et al., 1996).
126 Furthermore, these cropping systems (which are often critical for local food security) are
127 generally less well studied compared to the intensified mid-latitude agricultural systems that
128 have a greater global influence (Nendel et al., 2019).

129 The Agricultural Model Intercomparison and Improvement Project (AgMIP) was launched in
130 2010 to foster increased collaboration around crop model improvement across modelling
131 groups (Rosenzweig et al., 2013). Crop model intercomparisons have proven useful to
132 compare consistency among models and quantify uncertainty in model predictions (Asseng et
133 al., 2013; Bassu et al., 2014; Fleisher et al., 2017; Li et al., 2015; Ruane et al., 2017). They

134 have reinforced the benefit of multi-model approaches, as they help identify sources of
135 uncertainty (associated with model parameters, model structure, and model users) (Tao et al.,
136 2018, 2020). The ensemble mean or median usually resulted as best predictors for multiple
137 crops and for different soil and plant variables (Martre et al., 2015; Wallach et al., 2018). For
138 example, the intercomparison of maize models (Bassu et al., 2014) allowed assessing model
139 uncertainty in the simulated impact of climate change on maize yields under high-production
140 conditions, *i.e.* high-input, near-potential crop growth conditions where N fertilizer inputs
141 ranged from 60 to 255 kg N ha⁻¹ and sites were irrigated or had good rainfall and thus grain
142 yield ranged from 5 to 11 t ha⁻¹. These conditions differ considerably from the context of
143 smallholder farmers across SSA. Bassu et al. (2014) analyzed the effect of model structure
144 related to aboveground crop growth processes (*e.g.* simulation of net primary production of
145 the canopy as influenced by temperature and [CO₂]) but did not deal with soil-related
146 processes (*e.g.* N mineralization and N leaching).

147 Several studies relying on the calibration of a single crop model with field data, have
148 investigated model accuracy under current climate and explored the impact of climate change
149 on low-input smallholder systems in SSA (*e.g.* Amouzou et al., 2019; Freduah et al., 2019;
150 Rurinda et al., 2015; Traore et al., 2017). However, the use of a single crop model precludes
151 an analysis of simulation uncertainty related to model structure. A few studies investigated
152 climate change and N input interactions in smallholder context with two different crop models
153 (Faye et al., 2018b; Guan et al., 2017). Although these studies did address the issue of model
154 uncertainty, they did not embrace the wide diversity of existing crop models. The AgMIP
155 Global Gridded Crop Model Intercomparison study has conducted a series of model
156 sensitivity tests to [CO₂], temperature, water, and N conditions (Franke et al., 2020), but the
157 applied models operated on a macro-level (~0.5 degree spatial resolution) and were not
158 calibrated against field data to capture the conditions of controlled field experiments in SSA.
159 Thus, the accuracy and uncertainty of model simulations and model responses to the
160 interactions between N supply and climate change in low-input systems have not been
161 assessed for multi-model ensembles. Understanding climate change and N fertilizer input
162 interactions will help prioritize relevant recommendations for adaptations to climate change
163 for African smallholder farmers who currently use low levels of N inputs but will likely
164 intensify their cropping systems with additional mineral fertilizers (Vanlauwe et al., 2014).

165 This study addresses three main questions, namely: (i) What is the accuracy and uncertainty
166 of current crop model simulations of maize yield and other intermediary variables for field

167 experiments in the context of rainfed smallholder systems in SSA? (ii) How does N fertilizer
168 input interact with maize response to climate change (increase in [CO₂], increase in
169 temperature, and changes in rainfall)? (iii) Does model structure (*i.e.* formalisms to account
170 for N dynamics) and model consistency (*i.e.* the ability to accurately simulate multiple
171 variables) explain the simulated interaction between climate change and N fertilizer input?
172 By doing so, we explore the hypotheses that (i) model simulations of existing maize
173 experiments in smallholder context in SSA are more uncertain with lower accuracy than
174 simulations of intensified cropping systems in temperate regions, (ii) crop models simulate a
175 lower impact of [CO₂], temperature and rainfall changes in low-input (*e.g.* 0 kg N ha⁻¹) than in
176 high-input conditions (*e.g.* 160 kg N ha⁻¹), and (iii) model structure and consistency of
177 simulations for multiple soil and plant variables can explain diverging responses to the
178 interaction between N inputs and climate change.

179

180 **2. Materials and methods**

181 **2.1. Experimental data**

182 We searched the literature for peer-reviewed publications in which maize field experiments
183 under rainfed conditions were conducted during at least two cropping seasons in
184 representative maize growing areas in SSA. The studies needed to include measurements of
185 crop phenology (flowering and maturity dates), final grain yield and aboveground biomass at
186 maturity, and in-season soil water dynamics for at least one growing season. Studies chosen
187 represent a diversity of climates, soils and management conditions found across SSA for
188 maize production. This resulted in the selection of five experimental studies that were
189 conducted at sites respectively in Benin, Mali, Ghana, Rwanda and Ethiopia (Figure 1 and
190 Table 1). Besides the required data on crop phenology, grain yield, aboveground plant
191 biomass, and in-season soil water dynamics, data on in-season leaf area index (LAI) was
192 available in at least one of the two seasons at each site except Benin. Benin and Ghana also
193 included additional measurements of aboveground plant N accumulation during crop growth
194 (Benin) and at maturity (Benin and Ghana). Cultivars differed across sites and were open-
195 pollinated varieties, except in Ethiopia where a hybrid was grown. Total applied N fertilizer
196 was 0, 64, 80, 85 and 87 kg ha⁻¹ in the sites in Benin, Rwanda, Ghana, Mali and Ethiopia,
197 respectively. There was no irrigation at any of the sites (Table 1). The experiments were
198 extensively described, for Benin by Amouzou et al. (2018), for Mali by Traore et al. (2014),
199 for Ghana by MacCarthy et al. (2015), for Rwanda by Ndoli et al. (2018) and for Ethiopia by

200 Sida et al. (2018). Soil water content to maximum rooting depth was expressed as a
201 percentage of plant available soil water capacity (PAWC), which was calculated as the
202 difference between the water content at the drained upper limit (DUL) and the water content
203 at the lower extraction limit of the maize crop (LL) (both over the maximum rooting depth)
204 (Table 1 and Table S1). The soil initial conditions (moisture and mineral N) for the
205 simulations are given in Table S1.

206 To characterize each experiment regarding soil fertility, total available mineral N during the
207 crop growing season was estimated by summing (i) measured soil mineral N prior to sowing
208 (0-30 cm topsoil layer), (ii) N inputs from mineral fertilizer applied and (iii) N mineralized
209 from soil organic N in the topsoil (0-30 cm) and from manure applied. Manure was applied in
210 Mali only (Table 1). Nitrogen mineralized from soil organic matter and applied manure was
211 estimated considering a mineralization rate of 1.5% of soil organic N per growing season,
212 corresponding to commonly reported average mineralization rates in SSA (Bationo et al.,
213 2007; Masvaya et al., 2017). While PAWC and the 1.5% mineralization rate were used to
214 describe the experimental settings, this information was not forwarded to the modelling
215 groups and they were left to address PAWC and soil N availability as per their model usual
216 procedure.

217 Weather data (daily solar radiation, minimum and maximum temperatures and rainfall) for the
218 years of the experiments were obtained from records at on-site meteorological stations at all
219 sites. Wind speed and relative humidity for the years of the experiments were obtained from
220 the AgMERRA climate dataset (Ruane et al., 2015). For the model simulation of the baseline
221 climate (1980-2010), daily solar radiation, minimum and maximum temperatures and rainfall
222 were obtained from records at the on-site meteorological stations in Benin, Mali, and Ghana
223 and obtained from AgMERRA in Ethiopia and Rwanda. Wind speed and relative humidity
224 were obtained from AgMERRA for the baseline climate at all sites.

225 **2.2. Model characteristics and calibration procedure**

226 An ensemble of 25 crop models was used for this study (Table 2 and Table S2).

227 These crop models present structural differences in how they model crop growth and soil
228 processes (e.g. leaf area and light interception, grain yield formation, soil water dynamics,
229 nitrate leaching, see Table 2). Of particular interest for this study was how models simulate
230 the effect of N supply on crop growth and yield. This aspect is described in section 2.4.2.

231 Model simulations were executed by individual modelling groups within AgMIP
232 (Rosenzweig et al., 2013). The model calibration entailed two phases, *i.e.* (i) partial and (ii)
233 full calibration. For partial calibration, minimum input values required to run the model were
234 provided, *i.e.* soil characteristics, initial soil conditions (moisture at all sites and mineral N for
235 Benin, Mali and Ghana), crop management (sowing date, mineral and organic fertilizer
236 inputs), weather, and observed flowering and physiological crop maturity dates (Table 1 and
237 Table S1). In the partial calibration phase, adjustment by modelling groups to observed values
238 was limited to setting the model parameters involved in the simulation of the time to anthesis
239 and time to maturity. For full calibration, all measured crop and soil variables of the
240 experiments (see section 2.1) were provided. Modelling groups could adjust the model
241 parameters they deemed relevant to improve the model fit to observed data, using their usual
242 methods (e.g. manual tuning or use of an optimization program). There was no knowledge
243 sharing between the modelers and the researchers who conducted the trials during the
244 calibration steps to guarantee that modelers from the different groups had an equal level of
245 information on the field experiments. All sites and growing seasons were used for model
246 calibration and no independent evaluation of simulations was performed. Each modelling
247 group used one unique crop model. The different versions of APSIM, DSSAT and
248 SIMPLACE-LINTUL (see Table 2) were each used by single modelling groups.

249 **2.3. Model response to [CO₂], temperature, rainfall and N fertilizer**

250 Responses of fully calibrated models to variation in [CO₂], temperature and rainfall were
251 assessed, in interaction with varying mineral N input levels. Baseline years (1980-2010) were
252 simulated with the crop management of the second growing season at each site (Table 1) for
253 three levels of N fertilizer (0, 80, 160 kg N ha⁻¹). Response to [CO₂] was analyzed for
254 imposed concentrations of 360 and 720 ppm. Response to temperature was assessed by
255 increasing daily minimum and maximum temperatures by 4 °C. Response to rainfall was
256 analyzed by multiplying baseline daily rainfall by 0.5 and 1.50. These levels represent drastic
257 but plausible changes in environmental conditions that allow testing the sensitivity of crop
258 models (Rosenzweig et al., 2013). A doubling of [CO₂] (to 720 ppm) and a +4°C temperature
259 increase correspond to possible conditions around 2080 as predicted by climate models under
260 RCP 8.5 (IPCC, 2013). Factorial combinations of changes in [CO₂], temperature and rainfall
261 were not considered. For each level of [CO₂], temperature and rainfall, model simulations
262 were run for three levels of N fertilizer (0, 80, 160 kg N ha⁻¹ split in two applications during
263 the crop growing season).

264 2.4. Data analysis

265 2.4.1. Model accuracy, uncertainty, and response to climate change factors

266 We analyzed model accuracy for simulated grain yield, aboveground plant biomass,
267 maximum LAI, aboveground plant N at maturity, harvest index and in-season soil water
268 content. Observed and simulated values were compared using the Root Mean Square Error
269 (RMSE) and relative RMSE (rRMSE) for each of the above variables:

$$270 \quad RMSE_m = \sqrt{\frac{1}{n} \sum_{i=1}^n (O_i - P_{i,m})^2} \quad (1)$$

$$271 \quad rRMSE_m = \frac{RMSE}{\bar{O}} \times 100 \quad (2)$$

272 where O_i and $P_{i,m}$ are the observed and simulated values (for model m) for the i^{th}
273 measurement, n is the number of observations (*i.e.* the sum over sites, seasons, and over
274 measurement dates per site for in-season soil water content) and \bar{O} is the mean of the observed
275 values.

276 To analyze uncertainty in model simulations, the coefficient of variation (CV) of the
277 simulations with the 25 models for a given variable at a given site (both seasons) was
278 computed as:

$$279 \quad CV_s = \frac{\sigma_s}{\bar{p}_s} \times 100 \quad (3)$$

280 where σ is the standard deviation of the simulated values at site s and \bar{p} is the mean of
281 simulated values at site s . CV_s was also averaged across all sites.

282 We assessed the value of using an ensemble of models to simulate grain yield. We started by
283 computing the average simulated yields with ensembles of increasing number of models ($n=1$
284 to 25) for each of the ten experiments. Then we computed the relative variation between these
285 average simulated yields and the measured yield in the experiments:

$$286 \quad U_n = \frac{\sum_{i=1}^{10} |P_{ni} - O_i|}{\sum_{i=1}^{10} O_i} \times 100 \quad (4)$$

287 where O_i and P_{ni} are the observed and average simulated values (for a model ensemble of size
288 n) for the i^{th} experiment. Starting from two to 25 models, U_n was computed for a random
289 sampling of 5% of all the $\frac{25!}{n!(25-n)!}$ combinations of models. For $n=1$, all combinations were
290 evaluated.

291 The relative model response to a given climate change factor was computed for a particular
292 model as:

$$293 R_m = \frac{P_{future,m} - P_{baseline,m}}{P_{baseline,m}} \quad (5)$$

294 where $P_{future,m}$ is the 31-year (1980-2010) simulated average of model m for the variable of
295 interest (*e.g.* grain yield) under changed climate (altered [CO₂], temperature or rainfall, see
296 above) and $P_{baseline,m}$ is the 31-year simulated average of model m for the same variable under
297 the baseline climate (1980-2010). Here, we analyzed the relative model response to climate
298 change for doubling [CO₂] (360 ppm to 720 ppm), temperature +4°C, 50% of baseline rainfall
299 and 150% of baseline rainfall for N fertilizer applications of 0, 80 and 160 kg N ha⁻¹.

300 The relative model response to climate change R_m can take either positive or negative values.
301 Since the coefficient of variation between models is of limited value to assess prediction
302 uncertainty in this case, we calculated the Inter Quartile Range (IQR) of the ensemble relative
303 to change in the simulated variable of interest (*e.g.* grain yield).

304 **2.4.2. Model classification**

305 We first investigated whether model structural characteristics had an influence on the model
306 response to climate change with different N inputs. To do so, we classified the models
307 according to (i) their capability to simulate crop responses to N inputs, and (ii) the existence
308 of an N module with a daily time-step in the model (Table 2).

309 Two models (MCWLA and GLAM) did not handle crop response to N and formed the first
310 class. Three models (PEGASUS, SARRA-H and CELSIUS) simulated responses to N input
311 but did not include a detailed N module. These models formed the second class. In these three
312 models, a fixed N stress factor is applied to daily biomass production. In PEGASUS, values
313 of seasonal N stress factor were obtained by the correlation of national N fertilizer inputs and
314 gridded yield gap fraction data (Deryng et al., 2011). In CELSIUS and SARRA-H, a seasonal
315 N stress factor is calculated as the ratio of total seasonal available N to the crop N uptake
316 required for non-limited growth. In CELSIUS, total seasonal available N is calculated with
317 mineralization coefficients obtained from the literature (Riome et al., 2017). In SARRA-H,
318 the N stress factor was calibrated with on-farm and on-station experiments across West
319 Africa.

320 Twenty models handled crop responses to N and had a detailed N module with daily time-step
321 calculations of soil and plant N processes; they formed the third class of models (Table 2). All

322 class 3 models use as inputs (i) soil mineral N content at initiation of the simulation, and (ii)
323 the amounts of fertilizer N applied at specified dates during the cropping season. These
324 models include the explicit representation of a number of organic C pools in the soil (Table 2)
325 and functional processes of organic matter mineralization to compute the availability of
326 mineral N for crop uptake. In these models, daily mineralization of organic nitrogen is
327 simulated with one to seven organic carbon and nitrogen pools (Table 2) with specific
328 decomposition rates. Simple approaches usually identify a labile (fast decomposition rate) and
329 a stable (slow decomposition rate) organic matter pool. More complex models have additional
330 microbial biomass-related pools to simulate the role of soil organisms in the N mineralization-
331 immobilization turnover process during decomposition.

332 Within this third class of models, we investigated whether model consistency, *i.e.* model
333 ability to adequately simulate different soil and plant variables, could explain model
334 performances and model responses to climate change and its interaction with N fertilizer
335 inputs. The indicator used for model consistency was the sum of ranks (Martre et al., 2015)
336 for rRMSE over the variables of interest (*i.e.* grain yield, total aboveground biomass,
337 maximum LAI, total aboveground plant N, harvest index and soil water contents). Models
338 below the median sum of ranks for rRMSE over all the variables were classified as “most
339 consistent” models (class 3a), models above the median as “less consistent” models (class 3b)
340 (Table 2). An alternative ranking of models was computed based on the sum of ranks for grain
341 yield and total aboveground biomass only (the two variables available for all experimental
342 situations). Models below the median sum of ranks for rRMSE over these two variables were
343 classified as “highest ranked” models (for grain and biomass) (Table 2).

344 The effect of model class on the model response to climate change (doubling [CO₂],
345 temperature +4°C, 50% of baseline rainfall and 150% of baseline rainfall) was examined
346 using linear mixed model regression analysis with model class (3a or 3b) and N input as fixed
347 factors and site as a random factor. *P*-values to test the significance of model class were
348 obtained by likelihood ratio tests of the full regression model (including all fixed and random
349 factors) against a regression model with only N input and site effects. Visual inspections of
350 residuals plots did not reveal deviations from normality or heteroscedasticity. The analysis
351 was done using R (R Development Core Team, 2019; <http://www.R-project.org>, last accessed
352 13/07/2019) and the linear mixed-effect model was coded and tested with the R package *lme4*
353 (<http://cran.r-project.org/web/packages/lme4/index.html>, last accessed 16/07/2019). We
354 performed the likelihood ratio test with the *anova* function.

355 **3. Results**

356 **3.1 Characterization of sites and crop experiments**

357 Seasonal rainfall (from maize sowing to harvest) varied greatly across sites and seasons, from
358 217 mm (Rwanda, 2014 season) to 923 mm (Ethiopia, 2014 season) (Table 1). Seasonal
359 rainfall was low in Rwanda in 2014 but residual soil water at sowing was substantial (i.e. 57%
360 of PAWC). Crop water stress occurred during the two experimental years in Rwanda (Figure
361 1B). In Benin, Mali and Ethiopia, observed soil water contents never went below 50% of
362 PAWC during crop growth in the experiments where soil water was monitored (Figure 1B),
363 indicating a likely low occurrence of crop water stress. In Ghana, water content was
364 monitored to 30 cm soil depth only, so these data were of limited value for analyzing water
365 stress. Overall, observed maize grain yields were not correlated to seasonal rainfall (Figure
366 S1), confirming the role of N (Figure 1C) and other crop growth limiting factors in
367 determining grain yield.

368 Estimated total available mineral N during the crop growing season varied widely across sites
369 (Figure 1C). It was lowest at the experimental site in Benin, where there was no fertilizer
370 input (Table 1). Total available mineral N was highest in the experiments in Rwanda, due to
371 fertilizer inputs and a high soil organic N content compared with the experiments in the other
372 sites (Table 1). Although maize yield tended to increase with estimated total mineral N
373 availability (see section 2.1), the correlation was not significant (Figure 1C).

374 **3.2 Model simulations of the experiments**

375 **3.2.1 Model accuracy**

376 When partially calibrated to phenology only, most models failed to accurately reproduce grain
377 yield variations across sites and experiments (Figure 2A); rRMSE averaged across models for
378 grain yield was 63% (Figure 2B). Full calibration greatly improved the models' ability to
379 reproduce observed grain yields (Figure 2A); rRMSE averaged across models decreased to
380 26% (Figure 2B). The median of the fully calibrated model ensemble closely approximated
381 observed grain yields (Figure 2A). Improvement in model accuracy with full calibration was
382 also important for aboveground biomass at maturity and maximum LAI but was more limited
383 for aboveground plant N at maturity and harvest index (Figure 2B). Maize phenology was
384 accurately simulated by the fully calibrated models, with rRMSEs of 8 and 13% for the
385 sowing-anthesis and anthesis-maturity durations respectively. Regarding the temporal
386 dynamics, the range of simulated values of in-season LAI, soil water content, aboveground

387 plant biomass and aboveground plant N mostly enveloped the observed values (Figure S3).
388 With exception of the 2013 season in Ethiopia, most models were able to reproduce seasonal
389 soil water dynamics, a crucial variable for simulating crop growth when water stress occurs.
390 The increase in soil water up to field capacity during (i) the vegetative crop phase in the field
391 experiment in Benin in 2015 and (ii) during the reproductive phase in the field experiment in
392 Mali in 2010 was well reproduced by most models. The decrease in soil water below 50% of
393 PAWC early in the season in 2014 and later in the season in 2015 in Rwanda was also well
394 simulated by most models. Main disagreements between model simulations and field
395 measurements occurred (i) in Rwanda in 2015, for which most models underestimated LAI
396 and overestimated aboveground plant biomass and (ii) in Ethiopia in 2013, for which all
397 models underestimated observed aboveground plant biomass and soil water. The latter may,
398 however, be due to errors in rainfall recording or poor calibration of the moisture probes used
399 to estimate soil water.

400 Nitrogen mineralized from soil organic matter and N leached below the root zone were not
401 measured in the field experiments so we could not assess model prediction accuracy for these
402 variables. The ensemble median of simulated N mineralization, averaged over the two crop
403 growing seasons, was 22, 20, 39, 43 and 38 kg ha⁻¹ in Benin, Mali, Ghana, Rwanda and
404 Ethiopia, respectively. These simulated values matched reasonably well with the empirical
405 estimates of N mineralization using a rate of 1.5% of soil organic N (see section 3.1), *i.e.* 16,
406 10, 32, 93 and 40 kg ha⁻¹ in Benin, Mali, Ghana, Rwanda and Ethiopia, respectively. The
407 ensemble median of simulated N leaching, averaged over the two crop growing seasons, was
408 11, 15, 2, 2 and 4 kg ha⁻¹ in Benin, Mali, Ghana, Rwanda and Ethiopia, respectively.

409 **3.2.2 Model prediction uncertainty**

410 Full model calibration resulted in a reduction of prediction uncertainty (expressed as CV), and
411 this reduction was larger for grain yield and aboveground plant biomass at maturity than for
412 the other plant-related variables (maximum LAI, aboveground plant N at maturity and harvest
413 index) (Figure 2C). Overall, there was no clear indication that model prediction uncertainty
414 was largest in the most constrained (N-limiting) sites (*e.g.* Benin, see Figure S2). Prediction
415 uncertainty was relatively low for maize phenology (full calibration), with a CV of 9% for the
416 sowing-anthesis duration, and 16% for the anthesis-maturity duration. Prediction uncertainty
417 of simulated N mineralization was large, both with partial (CV of 90%) and full calibration
418 (CV of 85%). A similar behavior was found for simulated N leaching, with CVs of 171 and
419 136% with partial and full calibration, respectively.

420 The average absolute difference between measured and simulated grain yield decreased
421 rapidly with the number of models considered in an ensemble (Figure 3). A least eight
422 calibrated models were needed to fall below a 13.5% threshold, *i.e.* the CV of measured yield
423 typically obtained in experimental plots (Taylor et al., 1999).

424 3.2.3 Model classification

425 Models of class 1 and 2 simulated grain yield accurately with rRMSE values equal to or
426 below 18% (Table 3). Some models of these classes also performed well for the other
427 variables (*i.e.* total aboveground biomass at maturity, maximum LAI, harvest index and soil
428 water) with rRMSE values close to or below 30%.

429 The ten “most consistent” models of class 3, *i.e.* models below the median sum of rank for
430 rRMSE across all variables (Figure S4) were grouped in class 3a, and the others were placed
431 in class 3b (Table 2). The most consistent crop model (DNDC) when considering all variables
432 had a sum of rank of 32 (Table 3). Decrease in model uncertainty from partial to full
433 calibration for simulated grain yield was similar for both model classes 3a and 3b, *i.e.* 57 and
434 42% for class 3a and 3b respectively. However, the decrease in model uncertainty for
435 aboveground plant N at maturity was greater for models of class 3a than 3b, *i.e.* 44 and 11%,
436 respectively, indicating a likely greater effect of calibration on N supply and N uptake for
437 models of class 3a than 3b. After full calibration, class 3a models had a significantly ($P <$
438 0.05) smaller RMSE for grain yield, aboveground plant biomass at maturity, aboveground
439 plant N at maturity, maximum LAI, harvest index and in-season soil water content compared
440 with class 3b models. Most of the modelling groups (60%) who used class 3a models reported
441 calibration of soil parameters related to the size of the different soil organic matter pools to
442 adjust the amount of N mineralized from soil organic matter and to improve the match with
443 observed aboveground plant N, while only 10% of the class 3b modelling groups reported
444 such parameterization procedure (Table S3). Similarly, the majority (60%) of the class 3a
445 modelling groups reported calibration of parameters related to soil water dynamics (*e.g.*
446 moisture contents at field capacity and wilting point, soil water evaporation coefficients) to
447 mimic observed soil water dynamics, while only 30% of the class 3b modelling groups
448 reported such parameterization procedure (Table S3). Classifying class 3 crop models
449 according to grain yield and aboveground biomass only (*i.e.* the variables that were observed
450 for all sites and experiments) led to minor changes in the classification; the eight ‘most
451 consistent’ models were also among the eight best models when ranked based on grain yield
452 and aboveground biomass only (see underlined models in Table 2).

453 **3.3 Model ensemble response to climate change and N inputs**

454 Across sites and levels of N fertilization, the model ensemble median indicated a 4% increase
455 in grain yield for doubling [CO₂], 21% decrease with increasing temperature (+4°C), 1%
456 decrease with increasing rainfall (150% of baseline rainfall) and 17% decrease with
457 decreasing rainfall (50% of baseline rainfall). Nitrogen fertilizer input controlled to a large
458 extent the response to variation in [CO₂], temperature and rainfall (Figure 4). We describe the
459 interactions between N fertilizer input levels and climate change factors in the subsections
460 below.

461 **3.3.1 Variations in [CO₂] and temperature interact with N inputs**

462 The impact of increased [CO₂] on maize grain yield was smaller when N was limiting (Figure
463 4). With doubling [CO₂], the model ensemble median for the grain yield response was smaller
464 with 0 kg N ha⁻¹ (4% across all sites, *i.e.* 0.04 t ha⁻¹) than with 160 kg N ha⁻¹ (7% across all
465 sites, *i.e.* 0.29 t ha⁻¹). Model response varied across the sites (Table S4) and ranged between 0
466 and 5% for 0 kg N ha⁻¹, and between 4 and 13% at 160 kg N ha⁻¹.

467 Without N fertilization maize grain yield was less affected by higher temperature (+4°C)
468 compared with N fertilization (80, 160 kg N ha⁻¹) (Figure 4). Across all sites, the ensemble
469 median indicated a 14 and 26% decrease in grain yield as a result of increased temperature
470 with 0 and 160 kg N ha⁻¹, respectively. The negative effect of higher temperature was stronger
471 at the warm sites (Benin, Mali and Ghana) than at the cool sites (Rwanda and Ethiopia). With
472 160 kg N ha⁻¹, maize grain yield decreased by 29% in Benin, 32% in Ghana and 39% in Mali,
473 and by only 14% in Ethiopia and 16% in Rwanda (Table S4).

474 Prediction uncertainty, expressed here as the IQR of ensemble relative response in simulated
475 maize yield, was greater for temperature than for [CO₂] variation, without a clear indication
476 that uncertainty decreases with increasing N fertilizer inputs (Figure S5).

477 **3.3.2 Variation in rainfall in interaction with N inputs**

478 Comparing the effect of N fertilization under conditions of increased rainfall (150% of
479 baseline), grain yields of the 0 N treatment were more negatively affected than those with
480 inputs of 80 or 160 kg N ha⁻¹ (Figure 4). Across all sites, the model ensemble median
481 indicated a -8 and 0% change in grain yield caused by increased rainfall at 0 and 160 kg N ha⁻¹,
482 respectively. In Ethiopia, Mali, and Benin, an increase in rainfall had a strong negative
483 effect on grain yield, and the magnitude of this effect was stronger for low N conditions. The

484 ensemble median indicated a 7% decrease in Mali, a 16% decrease in Ethiopia and a 35%
485 decrease in Benin at 0 kg N ha⁻¹, and 0, -4 and -2% in those countries at 160 kg N ha⁻¹ (Table
486 S4). In Ghana, and Rwanda, increased rainfall had little effect on grain yield when no N was
487 applied (-2% and +1% relative yield change respectively) while positive effects of increased
488 rainfall occurred with 80 and 160 kg N ha⁻¹ (6 and 20% yield increase respectively).

489 Without N fertilization maize grain yield was less affected by a decrease in rainfall (50% of
490 current) than with N fertilization (80, 160 kg N ha⁻¹) (Figure 4). Across all sites, the model
491 ensemble median indicated a 2% and 27% decrease in grain yield with 0 and 160 kg N ha⁻¹,
492 respectively. Model response varied across the sites (Table S4). The impact of a decrease in
493 rainfall was lower for Ethiopia and Benin (20 and 4% yield decrease at 160 kg N ha⁻¹, Table
494 S4) than for Mali, Ghana and Rwanda (25, 36 and 50% yield decrease at 160 kg N ha⁻¹, Table
495 S4), which is consistent with the fact that Ethiopia and Benin had higher seasonal rainfall
496 (Table 1).

497 Prediction uncertainty, expressed here as IQR of ensemble relative response in simulated
498 maize yield, for rainfall variation was always higher at low input (0 kg N ha⁻¹) than at high N
499 input (80, 160 kg N ha⁻¹) with the exception of Mali for 50% of the baseline rainfall (Figure
500 S5). Decrease in model prediction uncertainty from low to high N input simulations was
501 generally greater for 150% relative rainfall than for 50% decrease in rainfall (Figure S5).

502 **3.3.3 Impact of model classification on model response to climate change in interaction** 503 **with N inputs**

504 Classifying the crop models (Table 2) allowed unravelling some of the variability related to
505 the interaction between climate change and N fertilizer inputs. Two models, MCWLA and
506 GLAM (class 1, Table 2), do not simulate responses to N inputs, and hence the interaction
507 between climate change and N input could not be analyzed (Figure 5). Three models
508 (PEGASUS, SARRA-H, and CELSIUS, see Table 2) simulate a response to N input but do
509 not include a detailed N module. These three models had different responses to climate
510 change and N input compared with the ensemble model responses described in sections 3.3.1
511 and 3.3.2. The simulated response by the SARRA-H model to increased [CO₂] was higher
512 under the zero N fertilization than under the 80 and 160 kg N ha⁻¹ fertilization in Mali. The
513 PEGASUS and CELSIUS models simulated very little interaction between increase in [CO₂]
514 and N fertilization. Similarly, the simulated impact of increased temperature (+4°C) by
515 SARRA-H was largest with the zero N fertilization in Rwanda, Ethiopia and Benin, *i.e.* the

516 opposite of the simulated trend by the model ensemble (see section 3.3.1). The PEGASUS
517 and CELSIUS models simulated also very little interaction between increase in temperature
518 and N fertilization. The three models (SARRA-H, PEGASUS and CELSIUS) simulated no
519 interaction between 150% of the baseline rainfall and N fertilization. The SARRA-H and
520 PEGASUS models simulated little to no interaction between 50% of the baseline rainfall and
521 N fertilization, while CELSIUS predicted an interaction consistent with the model ensemble
522 behavior. The response averaged across these three models is shown in Figure 5 (class 2
523 models).

524 The magnitude of model responses to some climate change factors was different between
525 class 3a (the ten most consistent models ranked using all the measured variables) and the “less
526 consistent” class 3b models (Figure 5). Simulated impact of doubling [CO₂] was significantly
527 lower ($P < 0.05$) for models of class 3a than for those of class 3b. The class 3a models
528 predicted a 0.9 and 5.3% increase in grain yield with doubling [CO₂] at 0 and 160 kg N ha⁻¹,
529 respectively, while the class 3b models predicted a 4.0 and 11.8% increase in grain yield. On
530 the other hand, simulated responses to changes in temperature and rainfall did not differ
531 significantly between class 3a and 3b models (Figure 5). When ranked based on grain yield
532 and aboveground biomass only (Table 2), highest ranked models did not differ significantly in
533 their response to [CO₂] and rainfall. The simulated response to increased temperature (+4°C)
534 was however significantly lower ($P < 0.05$) for highest ranked class 3a models (considering
535 grain and aboveground biomass) than for the lower ranked class 3b models.

536 Models of class 3 simulated N leaching, whereas models of the other classes did not. This
537 resulted in a stronger negative impact of increased rainfall on simulated grain yield, especially
538 for zero N fertilization, *i.e.* class 3 models simulated an increase in N leaching with an
539 increase in rainfall (Figure S6). The simulated increase in the amount of N leached with 150%
540 of baseline rainfall did not differ significantly between the model classes 3a and 3b. Models
541 of class 3 explicitly simulated N mineralization unlike the models of the other classes. They,
542 however, did not simulate an increase in N mineralization when temperature was increased
543 (Figure S7).

544 **4 Discussion**

545 *Low input systems and model accuracy and uncertainty*

546 Our comparative analysis of model accuracy with partial and full calibration confirms the
547 importance of calibration against observed harvest and in-season variables for accurate

548 simulation of maize growth and yield in smallholder context, as was the case in other model
549 intercomparisons (e.g. Asseng et al., 2013; Bassu et al., 2014; Li et al., 2015). However,
550 rRMSE for grain yield averaged over the fully calibrated models was greater (rRMSE = 26%)
551 for the cropping situations in our study with relatively low inputs than for e.g. high-input
552 situations in a wheat model intercomparison (rRMSE ~ 10%) (Asseng et al., 2013). This
553 confirms our initial hypothesis that model simulations are less accurate for low-input and
554 below potential yield situations where soil processes need to be adequately simulated. Model
555 ensembles gave greater accuracy than any model taken at random; in our study an ensemble
556 of at least eight randomly-selected models was needed to fall below the typical 13.5%
557 variation of measured grain yields in field experiments. This number is in line with the
558 findings of the previous maize, rice and wheat model intercomparison studies (Asseng et al.,
559 2013; Bassu et al., 2014; Li et al., 2015), and demonstrates the strength of model ensembles.
560 Model ensembles combine models that have complementary strengths in simulated plant
561 and/or soil processes and minimize errors in structure/parameterization that may exist for
562 some processes in individual models.

563 Model calibration for soil processes appeared to be key for low-input systems. For example, a
564 steep decrease in soil water content occurred during the growing season in the experiments in
565 Rwanda, the site with the lowest seasonal rainfall, and most models were generally able to
566 capture such behavior. Notably, modeling groups who reported the calibration of specific
567 parameters related to soil water dynamics to match observed soil water, achieved a greater
568 increase in accuracy from partial to full calibration (see section 3.2.3). A correct simulation of
569 soil mineralization was crucial for accurately simulating maize growth and yield in Benin as
570 no N fertilizer was applied. However, the lack of observations precluded the analysis of
571 model accuracy for N mineralization. The uncertainty in simulated N mineralization was large
572 and not reduced with full calibration, though some models did calibrate the sizes of the
573 organic matter pools and achieved a more accurate simulation of maize N uptake (see section
574 3.2.3). As expected, models simulated higher N leaching in the wetter sites (Ethiopia and
575 Benin), but without observations we could not analyze model accuracy with respect to
576 amounts of N leached. The large uncertainty in simulated N leaching was not reduced with
577 full calibration, and only one model reported changes in parameter values related to N
578 leaching with full calibration.

579 Our model classification indicated that the ‘most consistent’ models (class 3a) (see section
580 3.2.3) achieved a greater reduction in RMSE for aboveground plant N after full calibration,

581 hence increasing the likeliness of obtaining accurate simulations that consistently describe the
582 plant growth processes leading to grain yield (Martre et al., 2015). Eventually, the ‘most
583 consistent’ models simulated grain yield better, *i.e.* with a significantly smaller RMSE
584 compared with ‘less consistent’ models. Good calibration can however be impeded by data
585 availability, *e.g.* aboveground plant N was not measured in Mali, Ethiopia and Rwanda. Due
586 to imbalance in data availability between sites, modelers made assumptions on some inputs
587 and/or model parameters, leading to uncontrolled uncertainty in model simulations. When
588 detailed data on soil is limited, simple models with a limited number of parameters should
589 have an advantage over more complex models (Castañeda-Vera et al., 2015). Our findings
590 partly supported this argument. Class 3a models all used a simple “tipping bucket” model
591 approach for water dynamics, suggesting that the more detailed Richards equation for the
592 flow of water in unsaturated soils was not needed to simulate water stress in a satisfactory
593 manner. However, simple models with only one single pool for the simulation of organic
594 matter decomposition and associated N mineralization were not systematically among the
595 ‘most consistent’ models.

596 Data quality can also impede good model calibration (Kersebaum et al., 2015), *e.g.*
597 disagreement between (all) model simulations and soil water measurement in Ethiopia in
598 2013 points to issues with regard to rainfall input data, and/or soil water measurements,
599 and/or errors in the soil textural properties leading to higher predicted water percolation
600 through the soil profile.

601 *Low-input cropping systems and climate change impacts*

602 Our study revealed substantial interactions between N input and the effect of climate change.
603 With a doubling in [CO₂], the model ensemble median for relative grain yield response was
604 +7% across all sites at 160 kg N ha⁻¹ but only +4% at 0 kg N ha⁻¹. Such simulated increase at
605 high N fertilizer input is consistent with the previous maize model intercomparison study that
606 indicated a 7.5% yield increase with doubling[CO₂] (Bassu et al., 2014). The range of impacts
607 depending on sites was however narrower for our study, *i.e.* 4-13% compared with 0-19% in
608 Bassu et al. (2014), indicating possible improvements of some models that were used in both
609 studies (Table 2). In addition to a very small yet controversial direct effect of [CO₂] on C₄
610 crops photosynthesis (Leakey et al., 2006; Ziska et al., 1999), maize benefits from elevated
611 [CO₂] because of a “water-saving” effect (taken into account in the majority of the models,
612 see Table 2) due to reduced stomatal conductance and plant transpiration (Durand et al.,
613 2018). The associated increase in plant growth as a result of this effect requires greater rates

614 of N uptake and assimilation by the plant (Bunce, 2014; Stitt and Krapp, 1999). The maize
615 model ensemble simulated smaller gains from elevated $[\text{CO}_2]$ at 0 kg N ha⁻¹ than at higher
616 rates (160 kg N ha⁻¹), because the beneficial effects of elevated $[\text{CO}_2]$ were constrained by N
617 stress when no fertilizer was applied (Figure 4). Chamber-based and free-air CO_2 enrichment
618 experiments for maize were most often conducted under optimal nutrient supply in temperate
619 climates (Allen et al., 2011; Chun et al., 2011; Manderscheid et al., 2014). An exception is the
620 study of Bunce (2014) that showed lower maize yield response to elevated $[\text{CO}_2]$ as N
621 fertilization decreased, in line with our model estimates of the impact of elevated $[\text{CO}_2]$ for
622 different N fertilization levels.

623 When N availability was limiting plant growth under 0 kg N ha⁻¹, maize models simulated
624 only minimal impact of higher temperature and reduced rainfall, *i.e.* N stress made climate
625 stresses less prominent. These model results are (i) supported by experimental data showing
626 that crops with low supply of nutrients are less exposed to water stress (Affholder, 1995;
627 Rötter et al., 1997) and (ii) in line with other modelling studies showing a less negative
628 impact of climate variability and change in cropping systems with lower inputs (Affholder,
629 1997; Faye et al., 2018b; Rurinda et al., 2015; Sultan et al., 2014; Traore et al., 2017). The
630 “Liebig law of the minimum” helps understand such pattern: growth is dictated not by total
631 resources available, but by the scarcest resource (limiting factor). Besides, low nutrient supply
632 causes lower leaf area index and, therefore, less transpiration compared with crops grown
633 under non-limiting nutrient supply, leading to a lower soil water uptake by the crop and
634 consequently less impact of drought stress when rainfall becomes insufficient (Affholder,
635 1997; Faye et al., 2018b).

636 An increase in average temperature impacts maize grain yield mainly through a reduced
637 duration of the crop cycle and associated lower biomass accumulation and thus N uptake, a
638 process well accounted for in current maize models (Bassu et al., 2014). We could not find
639 any experimental work studying possible effects of N supply on crop growth duration. The
640 lower impact of temperature under low N fertilizer input was not due to an increase in N
641 mineralization and soil N availability: the models did not simulate increased N mineralization
642 under increased temperature (see section 3.3.3 and Figure S7). Although higher temperatures
643 are known to lead to an increase in N mineralization (Gutiñas et al., 2012), in the model
644 simulations a decrease in topsoil moisture may occur as a result of increased soil water
645 evaporation with increased temperature, thus reducing N mineralization rate and offsetting the
646 increased mineralization due to the rise in temperature.

647 Maize was more affected by a projected increase in rainfall when N was limiting (0 kg ha^{-1}).
648 We attribute this effect to the simulated increase in N leaching with increased rainfall, in line
649 with another modelling report in a smallholder context in West Africa (Freduah et al., 2019).
650 Simulated increase in N leaching with increased rainfall is supported by field experimental
651 studies on tropical soils in Eastern and Southern Africa, that observed highest N leaching in
652 growing seasons with highest rainfall amounts (Kamukondiwa and Bergström, 1994;
653 Mapanda et al., 2012; Russo et al., 2017).

654 Overall, the site influenced the impact of climate change. Maize growth and yield in the
655 cooler high altitude sites, *i.e.* Rwanda and Ethiopia, were less affected by increase in
656 temperature, in line with other studies predicting smaller crop yield losses, and in some
657 situations even gains at cooler locations (Waha et al., 2013; Bassu et al., 2014; Zhao et al.,
658 2017). At low N fertilizer inputs, maize at the site with the highest level of soil organic carbon
659 (*i.e.* Rwanda, see Table 1) was less affected by an increase in rainfall and the associated N
660 leaching, highlighting the crucial role of soil organic matter in the steady provision of N in
661 low-input cropping systems (*e.g.* Wood et al., 2018). Maize yield at sites with higher seasonal
662 rainfall (*i.e.* Benin and Ethiopia) was less affected by the simulated decrease in rainfall,
663 highlighting the importance of current climate conditions when analyzing the impact of
664 climate change (Waha et al., 2013).

665 We found no evidence that model uncertainty regarding the response to elevated $[\text{CO}_2]$ and
666 temperature would be greater at low levels of N input. However, uncertainty of model
667 response to rainfall change decreased (except in Mali) with the level of N fertilization,
668 indicating that models differed in the way they dealt with this interaction. The high variability
669 in simulated soil N mineralization (see section 3.2.2) explains to an extent such uncertainties.

670 *Influence of model structure on simulated crop responses to climate change*

671 Our analysis of crop model response to climate change coupled with experimental work
672 suggests that accurately accounting for both N supply and N leaching **under different**
673 **experimental conditions** is crucial for modelling climate change impacts on maize growth in
674 SSA. By separating models into classes, we disentangled some of the variability in model
675 response to climate change under contrasting N fertilizer inputs. Most models without a daily
676 N module (models of class 2) did not account for the interactions in the case of increased
677 $[\text{CO}_2]$ and change in rainfall in a way that was consistent with experimental evidence (see
678 section 3.3 and discussion above). Class 3a models (ranked based on rRMSE for all the

679 observed variables) simulated a smaller impact of elevated [CO₂] on maize yield irrespective
680 of the N input levels. There were, however, no obvious structural model characteristics
681 differentiating these best models from the others. For light utilization, models using a
682 “radiation use efficiency” approach or a “gross photosynthesis – respiration” approach were
683 represented equally within the two classes. Similarly, models with specific formalisms to
684 compute grain number were represented in the two classes. Class 3a models also simulated
685 more accurately crop response to N input than the other models (see section 3.2.3); therefore,
686 their simulation of the impact of climate change with contrasting N inputs is expected to be
687 more robust. Ranking models based on various plant and soil variables may however be
688 disputable since each variable has a different degree of importance for modelling crop growth.
689 For this reason, we investigated an alternative ranking based on grain and biomass yield only.
690 With this approach, the highest ranked models simulated significantly less impact of an
691 increase in temperature irrespective of the N fertilizer level. There were, however, no obvious
692 model structural characteristics differentiating these highest ranked models from the others,
693 *e.g.* for the type of heat stress simulated or the formalism for crop phenology. It should,
694 however, be noted that uncertainty in calibration due to model user subjectivity can
695 sometimes hide the role of specific model structures (Confalonieri et al., 2016). For example,
696 the PHINT parameter (interval between successive leaf tip appearances) in the DSSAT model
697 can be optimized to improve accuracy in LAI and grain yield simulations (Table S3). Whether
698 such optimization without detailed leaf appearance data to calibrate against is a good practice
699 is a point of debate. Identifying highest ranked models prior to simulation is challenging: a
700 given model will often obtain a different ranking for fit to the observations when used with a
701 different dataset (*i.e.* another combination of physical environment and management)
702 (Wallach et al., 2018). Without model validation with independent datasets (*e.g.* Confalonieri
703 et al., 2009), it is unlikely that the ranking proposed in this study holds for all possible
704 environments in a smallholder context. The ranking should therefore be seen as a means to
705 understand model behavior rather than a prescription on which model to use. Eventually, in
706 some cases model response may have been unrealistic, *e.g.* relative grain yield change with
707 doubling [CO₂] between 50% and more than 100% (*i.e.* outliers not shown in Figure 4).
708 Systematically discarding models with such unrealistic behavior could help in model selection
709 and improve ensemble model creation. However, such procedure remains in dispute as
710 discarding ‘extreme’ models can lead to overconfidence in models that behave in a similar
711 way, rewarding a convergence that may be the result of similar model assumptions and errors
712 (Knutti, 2010). Analysis of unrealistic behavior relying on relative changes also deserve

713 caution, as very small values with baseline climate can cause very large relative responses
714 with future climate even if the absolute responses are reasonable.

715 *Implications for sustainable intensification in SSA*

716 A substantial proportion of the farm households in SSA face food insecurity (Frelat et al.,
717 2016). Sustainable intensification with increased nutrient inputs and efficient use could
718 drastically increase crop production and improve household food availability, whilst
719 maintaining other important ecosystem services and preventing further land expansion (Loon
720 et al., 2019; Vanlauwe et al., 2014). Our modelling study indicates that farmers intensifying
721 maize production will face a different impact of climate change. With increased N
722 fertilization maize will benefit more from elevated [CO₂], but will be increasingly negatively
723 impacted as temperature increases and/or if rainfall decreases. The benefits from elevated
724 [CO₂] in mitigating drought impacts are unlikely to offset negative impacts from changes in
725 temperature and possibly rainfall (e.g. Faye et al., 2018b), so that yield penalties and larger
726 yield variability are expected. Increased yield variability may exacerbate the current risk of
727 unfavorable benefit-cost ratio for mineral fertilizer application (e.g. Bielders and Gérard,
728 2015; Falconnier et al., 2017). Policy interventions aiming at implementing risk coping
729 mechanisms and additional safety nets will therefore be crucial to support sustainable
730 intensification in the context of climate change.

731 Our findings have implications for developing recommendation domains for specific
732 adaptation strategies. In high rainfall sites like in Ethiopia and Benin, nitrate leaching will be
733 further intensified in case of a wetter climate; technologies maximizing N efficiency and
734 preventing losses through leaching, e.g. relay intercropping with deep rooting cover crops and
735 split applications of mineral fertilizer, may prove successful. In low rainfall sites like the site
736 in Rwanda, maize will experience more severe drought stress if climate gets drier; drought
737 tolerant cultivars and water-harvesting technologies (e.g. stone lines, tied ridging, zaï pits and
738 contour ridging) may help mitigate production losses. Low altitude warm sites (like in Ghana,
739 Mali and Benin) will be more affected by the rise in temperature so that breeding should aim
740 at cultivars adapted to heat stress.

741 *Avenues to extend the work*

742 Given the importance of accurately accounting for N dynamics when modelling the response
743 of low-input systems to climate change, further model improvement studies targeting these
744 systems should focus on (i) the evaluation of model ability to accurately simulate soil organic

745 matter mineralization, soil mineral N dynamics (*e.g.* leaching), plant N uptake and N stress
746 effects on crop growth by comparing simulations with observed data, and (ii) studying the
747 impact of model structure and complexity (*e.g.* ‘tipping bucket vs Richards equation, number
748 of soil carbon pools, impact of temperature and moisture on soil organic matter
749 mineralization) on the accuracy of model outputs. Comprehensive datasets to perform such
750 analysis currently do not exist for SSA. The research agenda on modelling the effects of
751 climate in low-input conditions should therefore aim at implementing detailed soil-crop
752 monitoring in experiments in contrasting sites representative of SSA. An experimental focus
753 on the interaction between N fertilization and elevated [CO₂] and temperature will also be
754 required, as models have not been tested against experimental data coming from tropical
755 environments for these interactions. Model sensitivity to rainfall was assessed in this study by
756 assuming a uniform relative change in daily rainfall throughout the growing season. More
757 complex patterns are likely to occur in the future, *e.g.* increase in the frequency and
758 magnitude of intense rainfall events (Taylor et al., 2017), or shortening of the rainy season
759 (Guan et al., 2017). More analyses of model responses that account for these complex patterns
760 are required. Most soils across SSA are highly weathered and inherently poor in P (Buerkert
761 et al., 2001). In three of the five experimental study sites (*i.e.* Mali, Ghana and Rwanda),
762 substantial amounts of P fertilizer (~25 kg P ha⁻¹) were applied, which is considered as
763 sufficient to reach about 70% of the water-limited yield potential (ten Berge et al., 2019;
764 Velde et al., 2014). With such amount of P fertilizer, it is unlikely that P stress was an issue in
765 these sites. For the other sites, accounting for P stress may help to reduce model uncertainty.
766 The number of models able to deal with P stress is however limited (*e.g.* Dzotsi et al., 2010).
767 Although maize is the most important staple food crop in large parts of SSA, other traditional
768 cereals such as sorghum and millet are also widely consumed in West and East Africa (OCDE
769 and FAO, 2016). Other crops such as cassava and banana also contribute substantially to food
770 security in sub-humid and humid SSA (OCDE and FAO, 2016). Extending model
771 intercomparisons of climate change impact for these other crops that are often cultivated in
772 environments different from the ones of our study sites would therefore allow for a more
773 comprehensive assessment of diverse smallholder farming systems and food security issues.
774 Besides, climate change is likely to strengthen pest and disease pressure on crops (Deutsch et
775 al., 2018). Although the soil-crop models used in this study do not account for biotic stresses,
776 considering this yield-reducing factor will be a necessary step towards a more integrated
777 assessment of the impact of climate change (*e.g.* Donatelli et al., 2017) on smallholder
778 farming systems.

779 **Conclusion**

780 Our modelling study revealed robust simulated interactions between climate change factors
781 and N fertilization and indicates that maize intensively managed with more N fertilizer will be
782 more sensitive to climate change. Therefore, the needed sustainable intensification of
783 cropping systems in SSA will become more and more risky as climate changes, which
784 highlights the need for policy interventions aiming at implementing risk coping mechanisms.
785 Predicting the impact of climate change on cropping systems in which N inputs are likely to
786 vary, requires crop models that explicitly account for N stress and N leaching. At least eight
787 fully calibrated models were needed to ensure reasonable accuracy in simulations.
788 Experimental data and model improvements are urgently needed to better evaluate the impact
789 of the interaction between (i) N fertilization and elevated [CO₂] and (ii) N mineralization and
790 elevated temperature. We advocate for a research agenda geared towards filling the current
791 data gap by implementing detailed and comprehensive soil-crop monitoring in contrasting
792 sites representative of agriculture in SSA.

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797 **Data sharing and data accessibility**

798 The data that support the findings of this study are available from the corresponding author
799 upon reasonable request.

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Figures:

Figure 1: (A), Map of sub-Saharan Africa showing the five study sites representative of FAO tropical agro-ecological zones where maize cultivation is possible. (B), Observed soil water content to maximum rooting depth in the six experiments where soil water was monitored (vertical lines from left to right are sowing, anthesis and maturity dates). PAWC: Plant Available Soil Water Capacity. (C), Observed maize grain yield at the five sites for two growing seasons (ten experiments) as a function of estimated available mineral nitrogen (N), *i.e.* the summation of initial soil mineral N, applied mineral and organic N and mineralized soil organic N and manure N over the whole growing season (for Ethiopia and Rwanda, initial mineral N measurements were not available)

Figure 2: (A), Observed (crosses with standard deviation if known) and simulated (box plots) grain yields. Simulations are from an ensemble of 25 partially and fully calibrated models. The line in the box and the width of the box are the median and the interquartile range respectively. The whiskers extend from the edge of the box to the most extreme data point below 1.5 interquartile range. Black open dots are outliers. (B) rRMSE (averaged across all models) of simulated – observed comparison for six variables of interest. For aboveground plant nitrogen the comparison was possible for four of the ten experiments only (Benin and Ghana). Open dots indicate rRMSE of ensemble median. (C) Coefficient of variation (averaged across sites) of 25 model simulations for five variables.

Figure 3: Relative variation (mean \pm standard deviation) between average of n models and measured grain yield in the ten experiments at five sites across sub-Saharan Africa. Models were randomly selected among the 25 calibrated models that simulated yield for the ten experiments. The horizontal dotted line is the 13.5% threshold, *i.e.* the coefficient of variation for measured yields typically obtained in experimental plots (Taylor et al., 1999).

Figure 4: Boxplots of relative change in grain yield (compared with baseline climate) when doubling $[\text{CO}_2]$, increasing temperature by $+4^\circ\text{C}$, increasing and decreasing rainfall (150% and 50% of baseline) in five sites across sub-Saharan Africa and for three N inputs of 0, 80 and 160 kg N ha^{-1} . Simulations are from 24 maize models with full calibration (one model did not perform the sensitivity analysis). Two models not simulating the effect of N on crop growth are displayed only for 160 kg N ha^{-1} . The line in the box and the width of the box are the median and the interquartile range respectively. The whiskers extend from the edge of the box to the most extreme data point below 1.5 interquartile range. Outliers (data points below $Q1 - 1.5 \times (Q3 - Q1)$ or above $Q3 + 1.5 \times (Q3 - Q1)$ where $Q1$ is the first quartile and $Q3$ the third quartile) were not displayed.

Figure 5: Mean (\pm SE) relative change in grain yield (compared with baseline climate) when doubling $[\text{CO}_2]$, increasing temperature by $+4^\circ\text{C}$, increasing and decreasing rainfall (150% and 50% of current) in five sites across sub-Saharan Africa and for three N inputs of 0, 80 and 160 kg N ha⁻¹. Simulations are from 25 maize models with full calibration classified in three classes: two models that did not simulate responses to N inputs (class 1, red), three models that simulated response to N inputs but without a daily N module (Class 2, green) and with a daily N module (Class 3). Models below the median sum of ranks for rRMSE over all the simulated variables were classified as “most consistent” models (class 3a, cyan), models above the median as “less consistent” models (class 3b, purple) (see section 2.3 for a detailed description of the classification). The reader is referred to the web version of this article for interpretation of references to colors.

Tables

Table 1: Characteristics of the five sites and ten experiments selected for model evaluation of maize yield simulation in rainfed smallholder farming systems across sub-Saharan Africa.

		Site				
General information	Country	Benin	Mali	Ghana	Rwanda	Ethiopia
	Location	Ouri Yori (Amouzou et al., 2018)	Ntarla (Traore et al., 2014)	Kpong (MacCarthy et al., 2015)	Bugesera (Ndoli et al., 2018)	Bako (Sida et al., 2018)
	Source					
	Latitude	10.82	12.58	6.16	-2.35	9.13
	Longitude	1.07	-5.70	0.06	30.27	37.10
	Elevation (m)	213	302	22	1400	1700-2000
		Tropic - warm semi-arid	Tropic - warm semi-arid	Tropic - warm sub-humid	Tropic - cool sub-humid	Tropic - cool - subhumid
	FAO AEZ					
	Rainfall pattern	unimodal	unimodal	bimodal	bimodal	unimodal
	Average growing season	june-september	june-september	march-july and august-december ¹	september-january and february-july ²	june-october
Soils	Soil type (FAO)	Gleyic Alisol	Ferric Lixisol	Vertisol	Humic Ferralsol	Nitisol
	Soil texture	loamy sand	loamy sand	clay	sandy loam	clay
	maximum rooting depth (cm)	60	120	100	100	120
	Plant Available Soil Water Capacity (mm to maximum rooting depth)	105	167	93	104	202
	SOC (%) (0-30cm)	0.28	0.2	0.57	1.65	0.65
	Total Nitrogen (%) (0-30cm)	0.023	0.015	0.048	0.138	0.059
	Management	Cultivar	EVDT-97 STR (OPV ³)	Suwan 1 - SR (OPV ³)	Obatampa (OPV ³)	ZM607 (OPV ³)
Sowing dates (DOY ⁴)		176, 185	151, 163	111, 105	282, 267	161, 158
Manure input (t/ha)		0	3	0	0	0
N content in manure (%)		-	1.6	-	-	-
Total applied N fertiliser (kgN/ha)		0	85	80	64	87
Total applied P fertiliser (kgP/ha)		0	26	30	20	9
Total applied K fertiliser (kgK/ha)		0	16	37	0	0
Phenology	Anthesis (DAP ⁵)	52, 53	56, 54	65, 60	72, 82	97, 98
	Maturity (DAP ⁵)	80, 86	97, 95	105, 106	120, 118	138, 139
Experimental year climate	Experimental year (first experiment)	2014	2009	2008	2013-2014	2013
	Mean growing season	27.9	26.6	27.7	22.8	21.1

	temperature					
	Mean growing season precipitation	516	549	536	217	476
	Experimental year (second experiment)	2015	2010	2009	2014-2015	2014
	Mean growing season temperature (season 2)	27.1	26.9	27.6	23.1	20.5
	Mean growing season precipitation (season 2)	810	705	455	351	923
Baseline climate (1980-2010)	Mean growing season temperature	25.5	28.3	27.6	21.9	20.6
	Mean growing season precipitation	641	582	442	331	939

¹Only March-July was considered for the experiments

²Only September-January was considered for the experiments

³Open pollinated variety

⁴Day of the year. First and second value indicate season 1 and season 2 experiments, respectively.

⁵Days after planting. First and second value indicate season 1 and season 2 experiments, respectively.

Table 2: Model grouping into four groups according to characteristics linked to the simulation of N and additional characteristics of the models. Class 3a and 3b were determined after the analysis of model ranking (based on rRMSE) when simulating all variables of interest (see section 2.4 for detailed description of the classification). In bold, models that participated in a previous maize intercomparison in high input systems (Bassu et al., 2014). Underlined models are the ten highest ranked models (among class 3 models) for grain and biomass simulation (see section 2.4 for detailed description of the classification).

Model Class	effect		Model	Model reference*	Leaf area development and light interconversions ^a	Light utilization ^b	Yield formation ^c	Crop phenology ^d	Root distribution over depth ^e	Simulation of N leaching	Simulation of heat stress	Type of water stress ^f	Type of heat stress ^g	Water dynamics ^h	Evapotranspiration ⁱ	Soil CN model ^j	Process modified by elevated CO ₂ ^k
	of N input	Daily N module															
1	no	no	GLAM	Challinor et al. (2004)	S	RUE,TE	B, HI	T, DL	LIN	no	yes	E	R	C	PT	-	RUE, TE
			MCWLA	Tao and Zhang (2010)	S	P-R	B, HI	T	EXP	no	yes	E	V,R	R	PM	-	-
2	yes	no	PEGASUS	Deryng et al. (2014)	S	RUE	B, Prt	T	LIN	no	yes	E, S	V,R	C	PT	C, P(1)	RUE, TE
			SARRA-H	Baron et al. (2005)	S	RUE	HI, Prt	T	LIN	no	no	S	-	C	PM	-	RUE, T
			CELSIUS	Ricome et al. (2017)	S	RUE	B, Gn, HI_mw	T, DL	LIN	no	yes	S	V,R	C	PM	N	RUE
3a	yes	yes	APSIM 7.9	Holzworth et al. (2014)	S	RUE	Prt	T, DL	EXP	yes	yes	S	V	C	PT	CN, P(3), B	RUE, TE
			DNDC	Smith et al. (2020)	S	TE	HI	T	EXP	yes	yes	S	R	C	PM	CN,P(5),B	PT
			HERMES	Kersebaum (2011)	D	P-R	Prt	T, DL, O	EXP	yes	no	E, S	-	C	PM	N, P(2)	LF, T
			DSSAT-IXIM-Maize+Century	Lizaso et al. (2011)	D	P-R	Gn	T, DL	EXP	yes	yes	E	R	C	PT	CN, P(2), B	RUE, T
			DSSAT-IXIM-Maize+Ceres-SOM	Lizaso et al. (2011)	D	P-R	Gn	T, DL	EXP	yes	yes	E	R	C	PT	CN, P(1)	RUE, T
			MONICA	Nendel et al. (2011)	D	P-R	Prt	T, DL, O	EXP	yes	yes	E	V	C	PM	CN, P(6), B	-
			SALUS	Basso et al. (2010)	S	RUE	HI, Prt	T, DL	EXP	yes	yes	E	V	C	PT	CN, P(3), B	-
			SIMPLACE-Lintul + ET Hargreaves + Heat stress with air temperature	Gaiser et al. (2013)	S	RUE	Prt	T, DL	EXP	yes	no	E, S	-	C	O	CN, P(7), B	RUE, TE
			STICS	Brisson et al. (2002)	S	RUE	B, Gn, HI,mw	T, DL, O	SIG	yes	yes	E	V,R	C	SW	CN, P(2), B	RUE, T
DSSAT-CERES-Maize+Century	Ritchie et al. (1998)	S	RUE	Gn	T, DL	EXP	yes	yes	E	R	C	PT	CN, P(2), B	RUE, T			
3b	yes	yes	AGRO-IBIS	Twine et al. (2013)	S	P-R	B, Prt	T	EXP	yes	yes	S	V,R	R	O	C, N, P(2)	F
			APSIM 7.10	Holzworth et al. (2014)	S	RUE	Prt	T, DL	EXP	yes	yes	S	V	C	PT	CN, P(3), B	RUE, TE

DSSAT-CERES-

Maize+Ceres-SOM	Ritchie et al. (1998)	S	RUE	Gn	T, DL	EXP	yes	yes	E	R	C	PT	CN, P(1)	RUE, T
EXPERT-N-Ceres	Biernath et al. (2011)	S	RUE	B, Gn	T, DL	EXP	yes	yes	E, S	V	R	PM	CN, P(3), B	-
EXPERT-N-Spass	Biernath et al. (2011)	D	P-R	Prt	T, DL	EXP	yes	yes	E, S	V	R	PM	CN, P(3), B	-
EXPERT-N-Sucros	Biernath et al. (2011)	D	P-R	Prt	T	EXP	yes	yes	E, S	V	R	PM	CN, P(3), B	-
MAZSIM	Kim et al. (2012)	D	P-R	HI, Prt	T, DL	CD	yes	yes	O	V,R	R	P, O	N, P(1), B	LF, T, F
RZWQM2	Sadhukhan et al. (2019)	S	RUE	B, Gn, Prt	T, DL, O	EXP	yes	yes	E, S	V,R	R	SW	C, N, P(1), B	PT
SIMPLACE-Lintul + ET														
FAO-56 + Heat stress with														
crop temperature	Faye et al. (2018a)	S	RUE	Prt	T, DL	EXP	yes	yes	E, S	R	C	PM	CN, P(7), B	RUE, TE
SWB	van der Laan et al. (2010)	S	RUE,TE	Prt	T	LIN	yes	no	S	-	C	PM	CN, P(4)	RUE, TE

^a S, Simple-unilayer (e.g. LAI); D, Detailed Multilayer (e.g. canopy layers)

^b RUE, radiation use efficiency approach; P-R gross photosynthesis - respiration; TE, compute water use first, then biomass growth from transpiration efficiency

^c HI, fixed harvest index; B, total (above-ground) biomass; Gn, number of grains; Prt, partitioning during reproductive stage; HI_mw, Harvest Index modified by water stress

^d Function of: T, Temperature; DL, photoperiod (day length); O, other water/nutrient stress effects considered

^e LIN, Linear; EXP, Exponential; SIG, sigmoidal; CD, Convective Dispersive

^f E = Eta/Etp, S = soil available water in root zone, O, leaf energy balance, leaf and soil water potential effects on photosynthesis and leaf expansion

^g V = vegetative (source), R = reproductive organ (sink).

^h C, 'Tipping bucket' capacity approach; R, Richards approach

ⁱ P, Penman; PM, Penman-Monteith; PT, Priestley-Taylor; SW, Shuttleworth-Wallace, O, leaf energy balance (MZ),

Hargreaves Dual crop coefficient method (SI2), water demand in plant, root water uptake, closes surface energy budget (AG).

^j C, C model; N, N model; P(x), x number of organic matter pools; B, microbial biomass pool.

^k LF, Leaf-level photosynthesis-rubisco or on QE and Amax; RUE, Radiation use efficiency; TE, Transpiration efficiency; PT, Photosynthesis and transpiration; F, Farquhar model, GY, Grain Yield; T, Stomatal conductance.

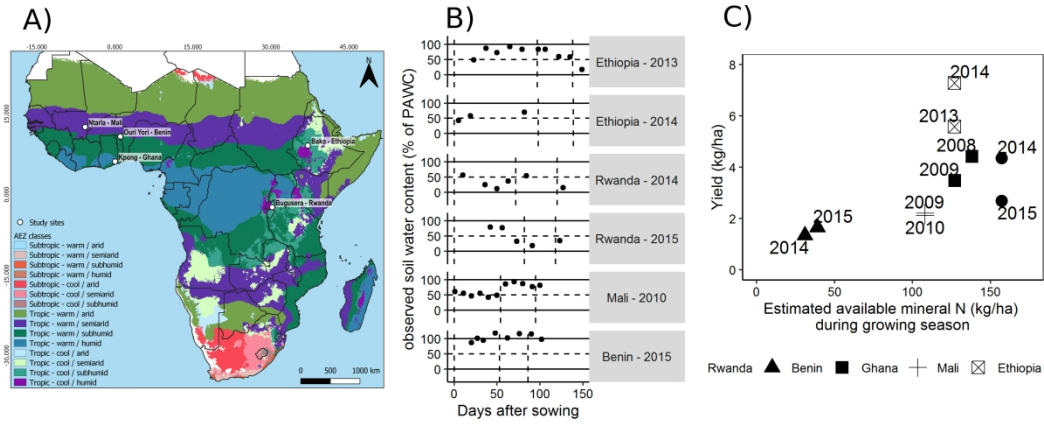
*More references and model documentation can be found in Table S2.

Table 3: rRMSE of simulated – observed comparison for six variables of interest for 25 fully calibrated maize models. In bold, models below median sum of ranks for all variables or yield and biomass only. Five models without daily simulation of N dynamics were not ranked.

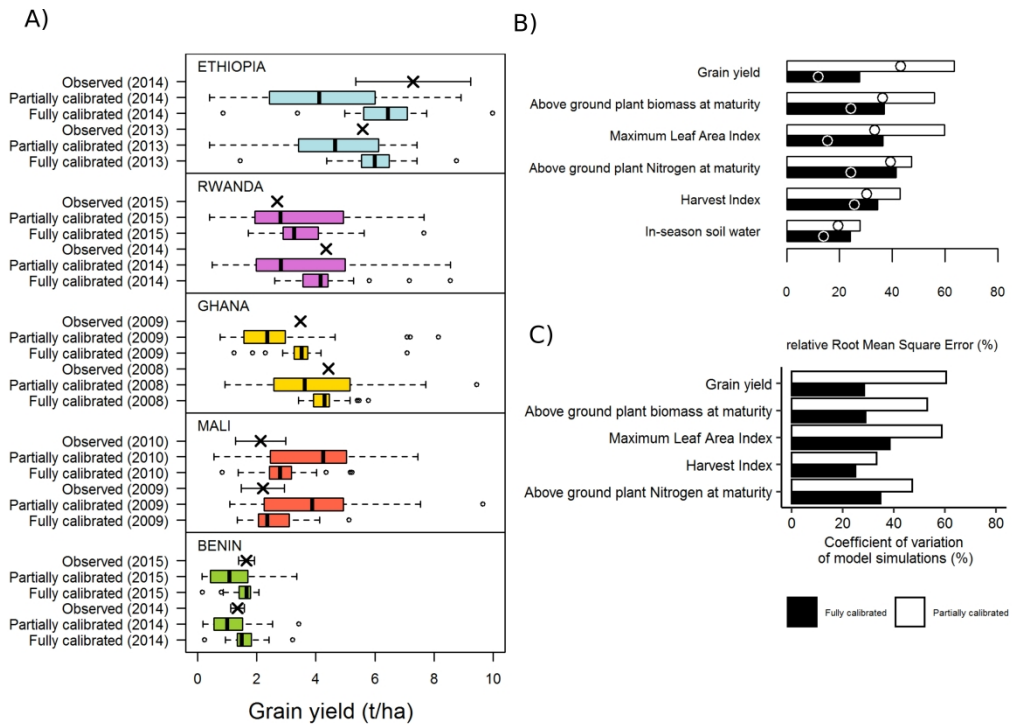
Model class	Model name	rRMSE (%)						Rank				
		grain yield	total above ground biomass	maximum LAI	total above ground plant N	Harvest Index	Soil water	Sum of ranks (all variables)	Sum of ranks (yield and biomass)	Final rank (all variables)	Final rank (yield and biomass)	
1	GLAMM	18	31	57	-	32	-	-	-	-	-	
	MCWLA	8	41	15	-	32	13	-	-	-	-	
2	CELSIUS	12	26	34	-	33	12	-	-	-	-	
	SARRA-H	17	31	10	-	34	17	-	-	-	-	
3a	PEGASUS	16	43	79	-	57	78	-	-	-	-	
	DNDC	22	34	40	7	21	9	32	20	1	9	
	STICS	8	26	13	52	23	22	42	6	2	1	
	HERMES	23	17	48	26	27	12	43	11	3	4	
	DSSAT-IXIM-Maize+Century	20	25	46	28	29	17	47	10	4	3	
	APSIM v 7.9	27	27	40	30	31	14	48	18	5	7	
	DSSAT-IXIM-Maize+Ceres-SOM	21	28	41	33	29	17	51	15	6	5	
	SIMPLACE-Lintul + Option 2*	11	30	6	43	38	24	54	10	7	2	
	MONICA	42	46	11	15	30	18	60	35	8	16	
	SALUS	36	48	6	11	41	23	73	35	9	15	
3b	DSSAT-CERES-Maize+Century	34	33	58	52	31	14	75	24	10	10	
	MAZSIM	40	32	41	44	32	22	77	27	11	12	
	APSIM v7.10	15	36	41	58	33	26	78	17	12	6	
	DSSAT-CERES-Maize+Ceres-SOM	36	35	58	56	32	14	84	27	13	11	
	SIMPLACE-Lintul + Option 1**	42	48	45	30	34	18	85	38	14	18	
	EXPERT-N-Sucros	19	36	47	78	39	29	93	20	15	8	
	RZWQM2	40	54	48	50	41	19	99	37	16	17	
	SWB	72	58	37	49	37	43	99	42	17	20	
	EXPERT-N-Spass	29	46	43	56	54	32	103	28	18	13	
	AGRO-IBIS	82	47	28	51	50	72	104	39	19	19	
EXPERT-N-Ceres	27	67	61	96	41	30	116	33	20	14		

*ET Hargreaves + Heat stress with air temperature

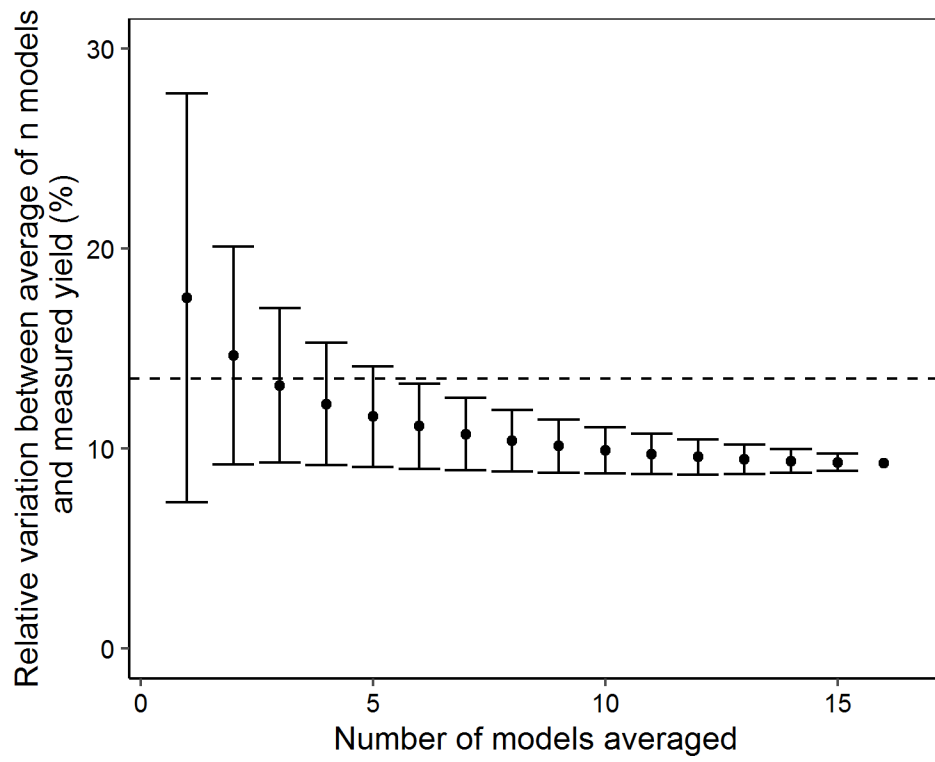
**ET FAO-56 + Heat stress with crop temperature



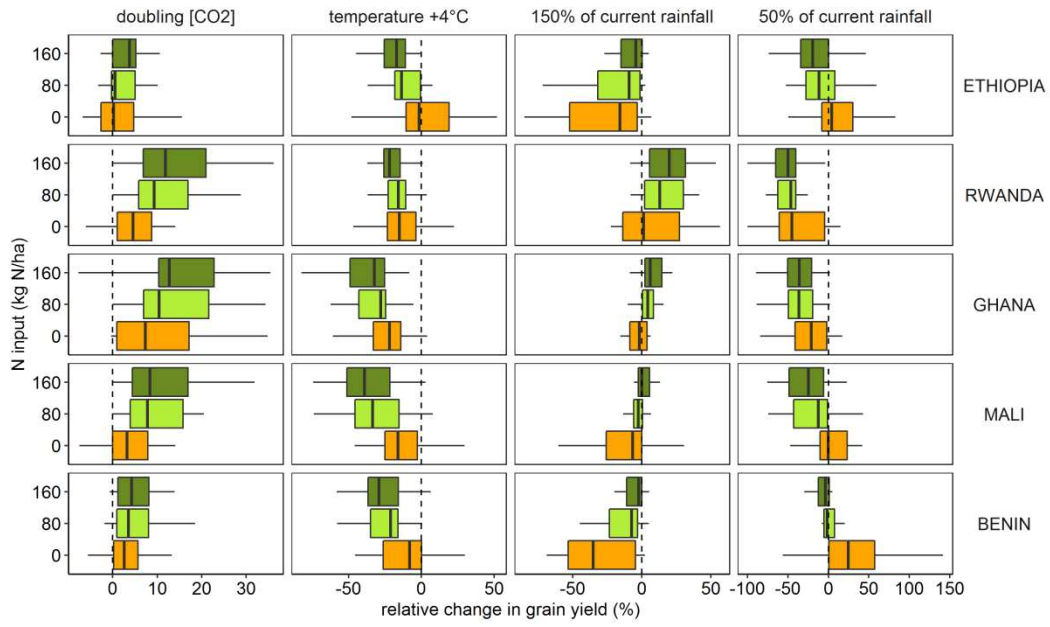
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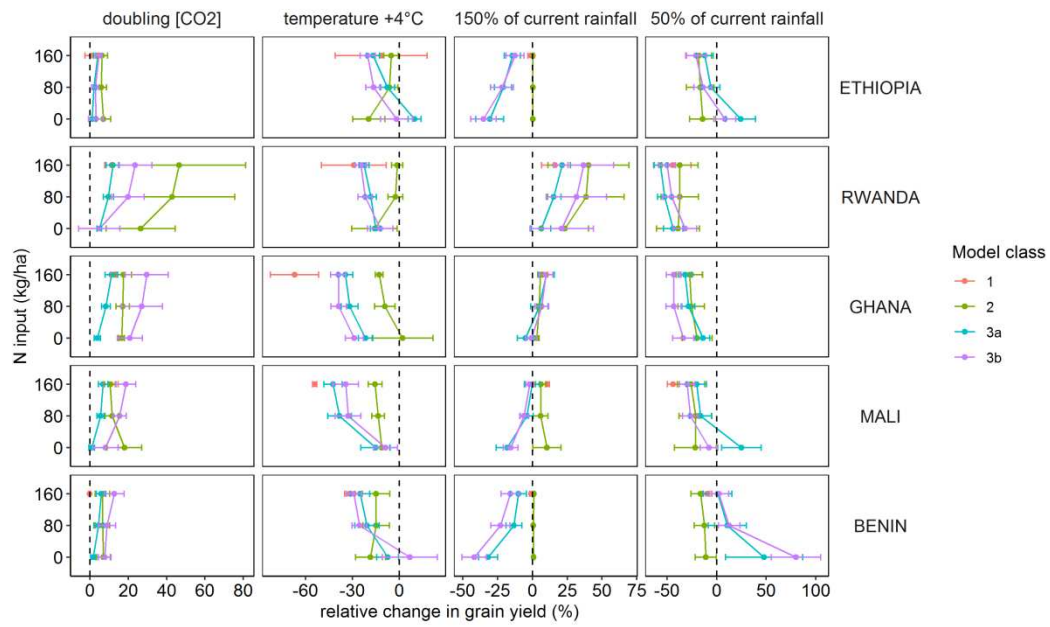
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