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# Designing cotton ideotypes for the future: Reducing risk of crop failure for low input rainfed conditions in Northern Cameroon

Romain Loison[a,*], Alain Audebert[b,c], Philippe Debaeke[d], Gerrit Hoogenboom[e,f,g], Louise Leroux[a], Palaï Oumarou[h], Edward Gérardeaux[a]

[a] CIRAD, UPR AÏDA, F-34398, Montpellier, France
[b] CIRAD, UMR AGAP, F-34398, Montpellier, France
[c] CERAAS, BP 3320, Thiès Escale, Senegal
[d] INRA, UMR AGIR, CS 52627, F-31326 Castanet-Tolosan Cedex, France
[e] College of Engineering, The University of Georgia, Athens, GA 30602, USA
[f] AgWeatherNet Program, Washington State University, Prosser, WA 99350-8694, USA
[g] Institute for Sustainable Food Systems, Frazier Rogers Hall, University of Florida, Gainesville, FL 32611, USA
[h] IRAD, BP 33 Maroua, Cameroon

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## ABSTRACT

Climate change is threatening the ability to grow cotton (*Gossypium hirsutum* L.) under low input rainfed production areas in Sub-Saharan Africa. In Northern Cameroon, yield has been declining due to unsuitable cropping practices such as sub-optimal planting dates, along with an absence in genetic gain. The aim of this study was to use a cropping system model (DSSAT CSM-CROPGRO-Cotton) to identify the best cultivars (ideotypes) for Northern Cameroon that are adapted to low input rainfed productions systems for 2050 under RCP4.5 and RCP8.5. Calibration and evaluation of the CSM-CROPGRO-Cotton were performed with field observations for two cultivars (Allen Commun and L484). For RCP4.5 and RCP8.5, 50 replications for 2050 were generated based on an ensemble of 17 Global Circulating Models. In total, 3125 virtual cultivars representing existing genetic variability for phenology, morphology and photosynthesis were simulated. Thereafter, they were evaluated for performance under the projected future climate based on potential yield and the resilience of yield to sub-optimal planting date. The widely cultivated cultivar L484 will be unsuitable under projected future climate, due to boll opening during the middle of the rainy season (median: 10/09 under RCP4.5 and 12/09 under RCP8.5). None of the ideotypes tested could optimize both yield and resilience (*Pearson* correlation $< -0.82$). However, compared to the current cultivar L484, two virtual ideotypes were identified: (a) "Ideo_sub" had a wide planting window, especially in the 10 worst replications of 2050, up to $+5$ days in RCP8.5; (b) "Ideo_Pot" had a high potential yield trait with low resilience to sub-optimal planting date, in the 10 worst replications of 2050, $+530\ \mathrm{kg\ ha^{-1}}$ in RCP4.5 and $+591\ \mathrm{kg\ ha^{-1}}$ in RCP8.5. Both ideotypes had an earlier anthesis date, a longer reproductive duration, and increase in the maximum photosynthetic rate. Therefore, breeding programs should consider these traits suggested by this system analysis using a crop simulation model for the identification of suitable cultivars under the projected future climate.

## 1. Introduction

Cotton (*Gossypium hirsutum* L.) is the major fiber crop grown in the world (ICAC, 2017). In West and Central Africa, more than 3 million metric tons of cotton were produced in 2014 (Fig 1). Cotton is an important source of cash income which contributes to the food security of millions of smallholder farmers (Tschirley et al., 2009). In addition, the residual effect of fertilizer applied on cotton improves the yield of succeeding staple crops (Ripoche et al., 2015).

However, climate change in tropical regions is expected to decrease yield and increase yield variability at the same time (Challinor et al., 2014). The use of optimal cultivars has been identified as the most efficient way to adapt to climate change (Challinor et al., 2014; Ramirez-Villegas et al., 2015). Optimal cultivars bred for a target environment are usually called ideotypes. They are described as "a combination of morphological and/or physiological traits, or their genetic bases, optimizing crop performance to a particular biophysical environment, crop management, and end-use" (Martre et al., 2015a).

* Corresponding author.
*E-mail address:* romain.loison@cirad.fr (R. Loison).

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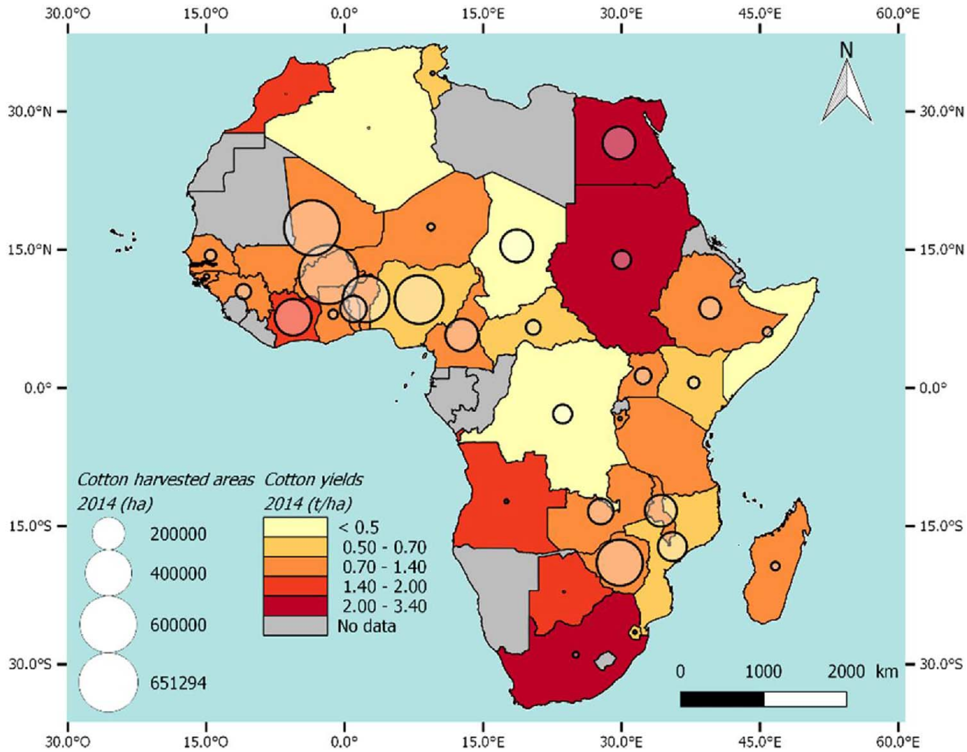


**Fig. 1.** Cotton harvested area and yield in Africa for 2014.
Source: FAOSTATS, September 2016.

Physiological breeding of ideotypes has already been demonstrated as efficient in increasing genetic gains under a wide range of environments for wheat (Reynolds and Langridge, 2016). As reviewed by Jeuffroy et al. (2014), breeding programs seeking for such ideotypes could be supported by cropping system models (CSM). The CSM dynamically estimate agricultural production (usually on a daily basis) as a function of weather, soil conditions and crop management. Hence, the CSM are theoretically able to represent Genotype x Environments x Management interactions (Jeuffroy et al., 2014). Among other applications, CSM were successfully used for optimizing planting date (Kim et al., 2013) and fertilization (García-Vila and Fereres, 2012), studying the impact of climate variability and climate change on production (Gérardeaux et al., 2013; He et al., 2015; Rötter et al., 2013; Xiao and Tao, 2014), and evaluating cultivars (Casadebaig et al., 2016; He et al., 2015; Xiao and Tao, 2014). The CSM have been used for the design of ideotype for cereals (Rötter et al., 2015; Stratonovitch and Semenov, 2015; Zheng et al., 2016; , 2012), rice (Paleari et al., 2017), peanut (Singh et al., 2014, 2012), sunflower (Casadebaig et al., 2011) and fruit trees (Quilot-Turion et al., 2012). Some CSM were successfully calibrated in African low input rainfed conditions for millet in Niger (Rezaei et al., 2014; Soler et al., 2008), peanut in West Africa (Singh et al., 2014) and cotton in Cameroon (Gérardeaux et al., 2013).

In Northern Cameroon, cotton is the main cash crop and it is exclusively grown by smallholder farmers under rainfed conditions (Sultan et al., 2010). The climate in Northern Cameroon is characterized by a very high spatial and temporal variability in rainfall (Fig. 2). There are both seasonal and intra-seasonal variabilities (M'Biandoun and Olina, 2006), which widely affect cotton yield, especially in the driest areas (Sultan et al., 2010). Spatial factors linked to climatic and soil conditions contribute to large differences in yields between the humid and the driest areas (1500 kg $ha^{-1}$ and 670 kg $ha^{-1}$, respectively; Tschirley et al., 2009). National cotton yield has been decreasing steadily since the 1980s (Naudin et al., 2010). This was mainly attributed to the absence of genetic gain on yield despite a dedicated breeding program (Loison et al., 2017), together with an increasing number of farmers using unsuitable cropping practices for cotton such as late planting, sub-optimal fertilization and cultivation of infertile plots because they allocate their limited resources (time, fertilizer and labor force) giving priority to the production of staple crops for personal consumption (Cao et al., 2011; Mahop and Van Ranst, 1997). This trend in yield is likely to worsen, as lower rainfall has been predicted because of climate change (Dai, 2012). In Northern Cameroon, cotton ideotypes, should be resilient to sub-optimal planting dates, low fertility and climatic variability and should prevent crop failure under climate change. To our knowledge, the use and evaluation of CSM for the design of rainfed cotton ideotypes under low fertility conditions in order to support breeders has not been documented. Therefore, the aim of this study, was to identify the traits of rainfed cotton ideotypes for Northern Cameroon under projected climate change conditions in 2050.

## 2. Material and methods

### 2.1. Model description

The CSM-CROPGRO-Cotton model of the Decision Support System for Agrotechnology Transfer (DSSAT) includes several modules: soil, weather, soil-plant-atmosphere, management, and crop (Jones et al., 2003). The soil module includes soil water (Ritchie, 1998), soil temperature, soil carbon model CENTURY suitable for low-input systems (Gijsman et al., 2002), and nitrogen dynamics (Godwin and Singh, 1998) in a one-dimensional vertical layers profile. The weather module uses daily weather data, with at least minimum and maximum air temperatures, solar radiation, and precipitation. The crop response to atmospheric $CO_2$ concentrations is simulated in DSSAT CROPGRO with similar impacts compared to those reported in the literature (up to 660 ppm, Alagarswamy et al., 2006). The soil-plant-atmosphere module computes daily soil evaporation and plant transpiration. The management module determines timing and characteristics of crop management (planting, tillage, harvesting, inorganic fertilization, irrigation, and application of crop residues or organic amendments). Finally, the crop module predicts the growth, development and yield of various crops. Each crop is described with its own set of genetic parameters. There are three sets of genetic parameters (species, ecotypes and cultivars) that account for differences in development, growth, and yield

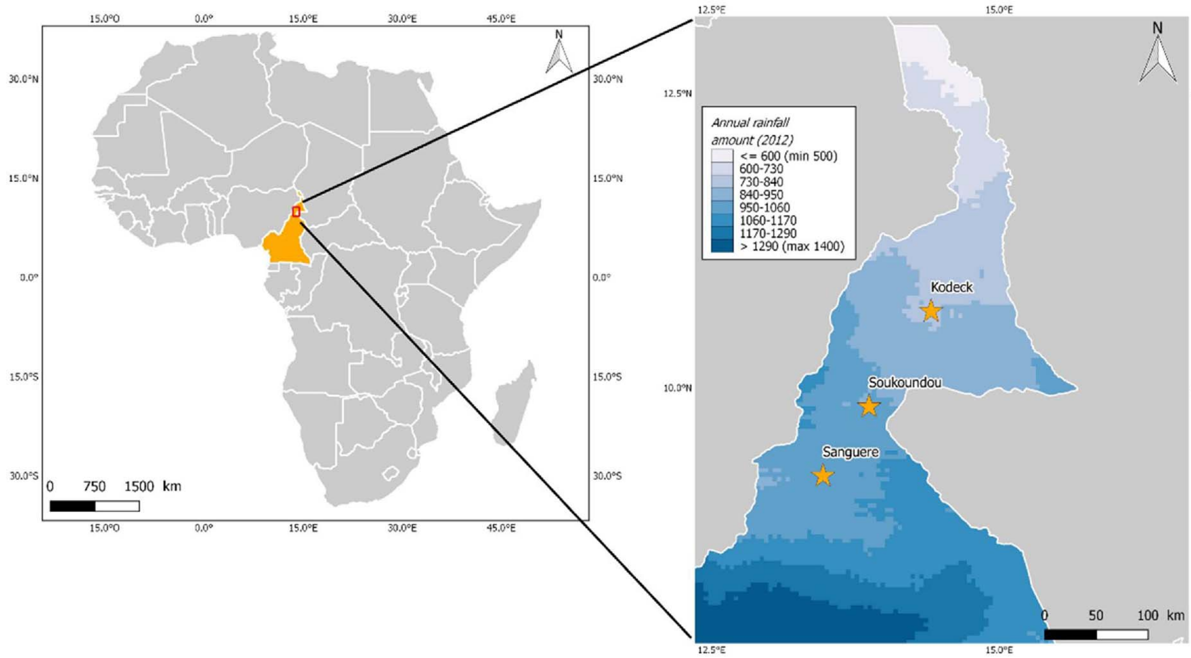


**Fig. 2.** Field experiments locations (yellow stars) and total rainfall in Northern Cameroon in 2012. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)
Source: TAMSAT.

between genotypes (Boote et al., 2003). Please see Pathak et al. (2007) and Thorp et al. (2014a) for a more comprehensive description of DSSAT CSM-CROPGRO-Cotton.

The CSM-CROPGRO-Cotton demonstrated appropriate responses of yield to water deficit, nitrogen deficit, planting density, planting date, and $CO_2$ enrichment (Thorp et al., 2014b). It has been applied under African rainfed conditions for cotton (Gérardeaux et al., 2013) and contains a wide range of genetic parameters which make it suitable for ideotype targeting using dynamic simulation. This study used DSSAT Version v4.6 (Hoogenboom et al., 2015).

## 2.2. Model calibration and evaluation

### 2.2.1. Experimental data

In Northern Cameroon, field experiments were carried out on Ulstafs soils (USDA soil taxonomy) on research stations in Sanguéré (9.25 N, 13.47 E) and Kodeck (10.65 N, 14.41 E) in 2012, and in Sanguéré and Soukoundou (9.84 N, 13.87 E) in 2013 (Fig. 2). In order to check whether Genotype (G) x Environment (E) interactions were accurately represented by the CSM-CROPGRO-Cotton model, two cultivars widely grown in Cameroon were compared in these experiments (Allen Commun released in Cameroon in 1950 and L484 in 2008, see Loison et al. (2017)). In all plots, plant density was 3.1 plants $m^{-2}$ with a row width of 0.8 m, insecticides were used to control bollworm (*Helicoverpa armigera*) and aphid (*Aphis gossypii*), and manual weeding was performed whenever needed. Differences in cropping conditions were due to differences in natural environments (onset of rainy season, soil properties, and precipitation pattern and amount), planting dates and fertilization levels (Table 1).

Synoptic weather stations located within 10 km from the field recorded temperatures, solar radiation, dew point temperature, and wind speed. Precipitation was measured daily in the field with a direct reading rain gauge (SPIEA type). Extensive measurements on the crop phenology (emergence, 1st true leaf, anthesis, boll opening), morphology (number of nodes, plant height), leaf area index, biomass (leaves, stems, reproductive organs), yield components and cotton yield were done. These measurements are described in Loison et al. (2017). In this study, cotton yield always refers to seed plus fiber yield (i.e. seed cotton yield).

### 2.2.2. Calibration and evaluation

Calibration and evaluation are two important steps prior to the use of CSM for simulations (Yang et al., 2014). Model calibration consists in fitting genetic parameters in order to reduce gaps between simulated and observed phenology, morphology, biomass, and yield variables. The indicator of gaps we used were the root mean square error (RMSE, Eq. (1)) and the relative RMSE (RRMSE, Eq. (2)).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (X_{obs,i} - X_{sim,i})^2}{n}} \quad (1)$$

$$RRMSE = \frac{RMSE}{\overline{X}_{obs}} \quad (2)$$

Where $X_{obs,i}$ and $X_{sim,I}$ are the observed and simulated values of the $i^{th}$ data pair, and $n$ the number of observed values, and $\overline{X}_{obs}$ is the average observed value.

The calibration and evaluation of CSM-CROPGRO-Cotton were conducted following the methodology described in Gérardeaux et al. (2013). All genetic parameters linked to crop phenology, leaf area index and growth of biomass from the cultivar file (COGRO046.CUL) were calibrated using GenSelect for DSSAT v46. The other parameters from the cultivar file, the ecotype file (COGRO046.ECO) and three parameters linked to water access from the species file (COGRO046.SPE) were calibrated by hand based on previous greenhouse and field experiments (Loison, 2015). Phenology was calibrated first, followed by leaf area index, biomass, and then cotton yield. Field experiments in 2012 were used for model calibration and those of 2013 for evaluation (Table 1). Calibration was considered successful when the anthesis date was predicted within 1 day from the observed date with a RMSE lower than 3 days and a RRMSE lower than 10%, 1st boll opening was predicted within 2 days from observed with a RMSE lower than 1 week and a RRMSE lower than 10%, maximum leaf area index RMSE was below 0.7 $m^2 m^{-2}$ and RRMSE below 25%, and cotton yield RMSE below 200 kg $ha^{-1}$ and RRMSE below 20%. Model evaluation was considered sufficient when the anthesis date was predicted within 1 day from the observed date with a RMSE lower than 3 days and RRMSE lower than

**Table 1**
Description of field experiments conducted in Cameroon in 2012 and 2013.

| | 2012 | | | | | 2013 | | | |
|---|---|---|---|---|---|---|---|---|---|
| Field | Sanguéré | | | Kodeck | | Sanguéré | | Soukoundou | |
| Soil texture | Loamy sand | | | Loam | | Loamy sand | | Sandy clay loam | |
| Soil water storage capacity | 206 mm | | | 84 mm | | 206 mm | | 150 mm | |
| Planting dates | 14-Jun | 27-Jun | 11-Jul | 6-Jul | 19-Jul | 8-Jul | 22-Jul | 4-Jul | 18-Jul |
| Fertilizer | | | | | | | | | |
| NPKSB (22 − 10-15-5-1%) | 11-Jul 200 kg ha$^{-1}$ | 19-Jul 150 kg ha$^{-1}$ | 31-Jul 100 kg ha$^{-1}$ | 31-Jul 100 kg ha$^{-1}$ | 14-Aug 200 kg ha$^{-1}$ | 26-Jul 200 kg ha$^{-1}$ | 16-Aug 100 kg ha$^{-1}$ | 30-Jul 200 kg ha$^{-1}$ | 13-Aug 100 kg ha$^{-1}$ |
| Urea (46%) | 31-Jul 50 kg ha$^{-1}$ | 08-Aug 50 kg ha$^{-1}$ | | | | 16-Aug 50 kg ha$^{-1}$ | 04-Sep 50 kg ha$^{-1}$ | 13-Aug 50 kg ha$^{-1}$ | 29-Aug 50 kg ha$^{-1}$ |

10%, and 1st boll opening was predicted within 2 days from observed with a RMSE lower than 1 week and RRMSE lower than 10%, maximum leaf area RMSE was below 0.7 and RRMSE below 25% and cotton yield RMSE below 450 kg ha$^{-1}$ and RRMSE below 33%.

### 2.3. Model simulations

#### 2.3.1. Generating virtual cultivars

In order to generate virtual cultivars (VC) with different phenotypes, we modified the values of CSM-CROPGRO-Cotton genetic parameters of L484 which govern the main plant functions: (i) phenology: phase duration before and after anthesis (respectively EM-FL and SD-PM, thermal days), (ii) photosynthesis: maximum assimilation rate (LFMAX, mg [$CO_2$] m$^{-2}$ s$^{-1}$) and specific leaf area (SLAVR, cm$^2$ g$^{-1}$), and (iii) light interception: maximum size of a fully expanded leaf (SIZLF, cm$^2$). For each of these five cultivar traits, five values evenly distributed were assigned from minimum (Table 2, Min used) to maximum (Table 2, Max used) in the existing range and all possible combinations of parameters values (cultivar traits x five values resulting in 3125 combinations) were simulated. The 3125 VC were compared to the cultivar L484 which is widely grown in Cameroon. The values of the parameters for all cultivars, including the virtual ones, are presented in Appendix A.

#### 2.3.2. Modelling management practices

We hypothesized that in 2050, the range of planting dates would not change as the onset of future rainy season is expected to be similar to the current situation (in June; Guan et al., 2017) while the length of growing season in northern Cameroon is likely to be reduced (Thornton et al., 2010) hence preventing earlier or later planting dates, respectively. However, we expect fertilizer use to be lower in 2050, due to increasing fertilizer costs, as observed over the last 65 years (fertilizer annual indices, World Bank, 2016). In order to account for a broad range of conditions, 45 planting dates were considered, ranging from 1st June to mid-July (window recommended to farmers by the cotton development company in Cameroon), similar to the approach used by Zheng et al. (2012). Plant density was 31250 plants ha$^{-1}$ with a row width of 0.8 m. Suboptimal fertilization of 22 kgN ha$^{-1}$ was applied 10 days after planting, similar to the recommendations for the Far North region in case of late planting. The soil used was the one at the experiment conducted in Kodeck, as it is the most drought prone site. Cotton was harvested at maturity.

**Table 2**
Range of variability for five cultivars parameters used in the simulations with the CSM-CROPGRO-Cotton model. The 3125 virtual cultivars were simulated by all possible combinations of five values evenly distributed between minimum (Min used) and maximum (Max used) of each parameter.

| Parameter | Min used | Max used | Range in other studies | Reference for CSM-CROPGRO-Cotton |
|---|---|---|---|---|
| EM-FL | 27.72 | 49.26 | 27.72–54.2 | Amin et al., (2017), Pathak et al., 2007 |
| SD-PM | 20.95 | 66.60 | 21.46–66.60 | Pathak et al. (2007), Wajid et al., (2014) |
| LFMAX | 0.70 | 4.09 | 0.70–4.09 | Pathak et al. (2012), Wajid et al. (2014) |
| SLAVR | 90.0 | 250.0 | 90–250 | Dzotsi et al. (2013), Pathak et al. (2007) |
| SIZLF | 200.0 | 340.9 | 200–300 | Adhikari et al. (2016), Anapalli et al. (2016) |

#### 2.3.3. Modelling the climate for 2050 under emission scenarios RCP4.5 and RCP8.5

In order to account for the uncertainty due to anthropic impact on climate, the climate for 2050 was generated with the stochastic weather generator MarkSim™ (Jones and Thornton, 2000) under two contrasting greenhouse emissions scenarios (RCP). The first scenario, RCP4.5 (Thomson et al., 2011), considers a stabilization of emissions, while the second scenario, RCP8.5 (Riahi et al., 2011), considers an increase in greenhouse gas emissions. For each RCP, 50 independent random samples (replications) of year 2050 were generated with MarkSim™ using a multi-model ensemble of 17 global circulating models (GCMs) from IPCC5 (see http://gisweb.ciat.cgiar.org/MarkSimGCM/docs/doc.html). MarkSim™ provides a good estimation of annual and monthly rainfall variance in tropical and subtropical regions (Jones and Thornton, 2000). The average sum of monthly rainfall by RCP for the cropping season are presented in Appendix B. Average temperature was 30.6 °C for RCP4.5 and 31.0 °C for RCP8.5. This generated climate for 2050 was used in the CSM-CROPGRO-Cotton model simulations with atmospheric $CO_2$ concentrations of 487 ppm under RCP4.5 and 541 ppm under RCP8.5 (Meinshausen et al., 2011).

In total, 14,067,000 simulations were run and evaluated (3126 cultivars * 45 planting dates * 50 replications of year 2050 * 2 RCPs).

### 2.4. Variables used for cultivar evaluation

For each RCP and replication of 2050 conditions, the virtual cultivars were evaluated based on two criteria. The first criteria was "the highest cotton yield simulated at optimal planting date ($Yield_{opti}$)". The second criteria was "the planting window (PW)", which is the number of planting days associated with the loss in cotton yield less than 148 kg ha$^{-1}$ compared to $Yield_{opti}$ (i.e. 20% of average cotton yield of reference cultivar L484 in RCP4.5). The PW can range from 1 day to 45 days. The PW was used as a proxy for cultivar resilience to sub-optimal planting date, extended PW being considered as more resilient and providing more flexibility to the farmers.

### 2.5. Statistics and method to select ideotypes

Data processing, statistical analysis and graphics were performed with the software R version 3.4.1 (R Core Team, 2017). Quality of model calibration and model evaluation were based on RMSE and RRMSE.

A state of crop failure was defined whenever the difference between the income generated from selling the cotton crop and the cost of production was negative, as shown in Eq. (3).

$$\text{Crop failure} = (\text{Cotton price x Yield} - \text{Cost of production} < 0) \quad (3)$$

The costs and prices used for the calculation of crop failure threshold are those of season 2004/2005 and were not extrapolated to 2050 as no such forecast is available. Nevertheless, by 2030, fluctuations in fertilizers costs and world market cotton prices ("Cotlook A index", used for *Cotton price* calculation (Bassett, 2014)) are forecast to remain below 10% of present values, with higher increase in world market cotton price than in fertilizers costs (World Bank, 2017). In 2004/2005, the average total cost of production of the most intensive cotton farmers in Cameroon was 190.27 US$ (*Cost of production*), which included agricultural inputs and hired service (Tschirley et al., 2009), the cost of family labor was not accounted for in our estimations because of data limitations (Peltzer and Röttger, 2013). Farmers sold their cotton at the price (*Cotton price*) of 0.32 US$ $ha^{-1}$ (Tschirley et al., 2009). Crop failure happens when the yield (*Yield*) is lower than 595 kg $ha^{-1}$ (Eq. (4)).

$$\text{Crop failure} = (\text{Yield} < 595\ \text{kg ha}^{-1}) \quad (4)$$

The candidate cultivars selected at the first step were those with a 1st quartile (Q1) of $Yield_{opti}$ higher than 595 kg $ha^{-1}$ in order to limit the risk of crop failure to 25% of years. Then, within these candidate cultivars, only the ones offering the best tradeoff between the two criteria were selected for further analysis (i.e. those Pareto optimal, code R in Appendix C).

## 3. Results

### 3.1. Model calibration and evaluation

Model calibration resulted in cultivar parameter estimates for the cultivars L484 and Allen Commun (Table 3). Phenology of the two cultivars was respectively calibrated and evaluated with a maximum RMSE of 1.2 days and 1.3 days for the duration between planting and emergence, 2.7 days and 2.5 days for the duration between emergence and anthesis and 6.8 days and 4.1 days for emergence to physiological maturity with a maximum RRMSE of 6% and 4% for emergence to physiological maturity (Table 4). Similarly, the number of nodes on the main stem, maximum leaf area index (LAI), and canopy height were properly calibrated and evaluated with a maximum evaluation RMSE of 2.3 nodes, 0.6 $m^2$ $m^{-2}$, and 13 cm, and evaluation RRMSE of 11%, 22%, and 13%, respectively. Finally, aerial biomass, harvest index, and cotton yield were, on average, well calibrated and evaluated with a maximum evaluation RMSE of 949 kg $ha^{-1}$, 11%, 435 kg $ha^{-1}$, respectively and evaluation RRMSE of 24%, 31% and 32.6%, respectively. The maximum ratio of seed cotton mass to boll mass showed a calibration RMSE of 11% and RRMSE of 16% and an evaluation RMSE of 7% and RRMSE of 11%. Overall, the calibrated model showed an acceptable performance when evaluated with the independent dataset for two cultivars and could thus be reasonably used for ideotype design.

### 3.2. Outcome of the simulations

#### 3.2.1. Summary information

Due to climate uncertainty reflected in the variability between 2050 replications, the $Yield_{opti}$ of reference cultivar L484 ranged from 226 to 1097 kg $ha^{-1}$ for scenario RCP4.5 and 272–1045 kg $ha^{-1}$ for scenario RCP8.5. Reference cultivar L484 showed similar average values of $Yield_{opti}$ for both RCPs (*Paired t-test, Pvalue* = 0.89, df = 49). Due to cultivar variability, the average $Yield_{opti}$ ranged from 78 to 1447 kg $ha^{-1}$ between cultivars for RCP4.5 and 90–1431 kg $ha^{-1}$ for RCP8.5. In addition, the Q1 of $Yield_{opti}$ ranged from 68 kg $ha^{-1}$ to 1214 kg $ha^{-1}$ for RCP4.5 and 74–1294 kg $ha^{-1}$ for RCP8.5.

Irrespective of the RCP scenario, the Q1 of planting window (PW) between cultivars ranged from 4 to the maximum number of planting days tested in this study (45 days). The average simulated length of L484 crop cycle (planting to boll opening) with was 99.4 days for RCP4.5 to 97.8 days in RCP8.5 leading to boll opening between September 2nd and October 23rd with median opening date on September 12th in RCP4.5 and September 10th for RCP8.5.

Irrespective of the RCP scenario, all CSM-CROPGRO-Cotton parameters were negatively correlated with Q1 of PW (Table 5). Similarly, all parameters but EM-FL were positively correlated with Q1 of $Yield_{opti}$. EM-FL was negatively correlated to Q1 $Yield_{opti}$ for both RCPs. The only strong correlation between parameters and the two criteria was for LFMAX. Q1 of $Yield_{opti}$ was strongly and negatively correlated to Q1 of PW with *Pearson's r* coefficients of −0.88 in RCP4.5 and −0.82 in RCP8.5 (both *P-values* < $10^{-4}$). Therefore, no cultivar had the best performance for both criteria. Some, were optimal for one criteria only and others had a tradeoff performance between the two criteria.

#### 3.2.2. First step of cultivar selection

Of the 3125 virtual cultivars (VC) generated, the majority were suboptimal and were therefore classified as "rejected" (Fig. 3). The rest were kept for further analysis and these represented either the optimum for one criterion or a tradeoff between the two criteria (noted as "candidate," Figure 3). There was no best virtual cultivar (i.e. a point at the top right corner). Out of the 3125 VC, 14 candidates were identified for RCP4.5 (Fig 3a) and 9 for RCP8.5 (Fig 3b) with 22 unique

**Table 3**
Values of genetic parameters of cotton cultivars L484 and Allen Commun calibrated for the CSM-CROPGRO-Cotton for northern Cameroon conditions.

| Parameter | Description | L484 | Allen Commun |
|---|---|---|---|
| *Cultivar parameters* | | | |
| EM-FL | Photothermal time between plant emergence and flower appearance | 48.4 | 49.3 |
| FL-SD | Photothermal time between first flower and first seed | 12.2 | 13.5 |
| SD-PM | Photothermal time between first seed and physiological maturity | 21.5 | 21.0 |
| FL-LF | Photothermal time between first flower and the end of leaf expansion | 51.9 | 46.8 |
| LFMAX | Maximum leaf photosynthesis rate ($mg_{CO2}$ $m^{-2}$ $s^{-1}$) | 2.39 | 2.60 |
| SLAVR | Specific leaf area under standard conditions ($cm^2$ $g^{-1}$) | 200 | 206 |
| SIZLF | Maximum size of full leaf ($cm^2$) | 300 | 341 |
| XFRT | Maximum fraction of daily growth that is partitioned to bolls | 0.84 | 0.70 |
| SFDUR | Photothermal time for seed filling under standard growth conditions | 58.0 | 53.9 |
| THRSH | Maximum ratio of seed cotton weight and boll weight | 71 | 70 |
| SDPRO | Fraction protein in seeds ($g_{protein}$ $g_{seed}^{-1}$) | 0.180 | 0.183 |
| SDLIP | Fraction oil in seeds ($g_{oil}$ $g_{seed}^{-1}$) | 0.176 | 0.179 |
| *Species parameters* | | | |
| RWUEP1 | Threshold ratio before drought stress of evaporative demand to root water uptake | 1.2 | 1.5 |
| RWUMX | Maximum root water uptake per unit root length ($cm^3_{water}$ $cm_{roots}$) | 0.08 | 0.04 |

**Table 4**
CSM-CROPGRO-Cotton calibration and evaluation across cultivars (Allen Commun and L484) in Cameroon.

| | Calibration (2012 dataset) | | | | | | | | Evaluation (2013 dataset) | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Allen Commun | | | | L484 | | | | Allen Commun | | | | L484 | | | |
| *Variables* | Obs [a] | Sim [b] | RMSE [c] | RRMSE [d] | Obs | Sim | RMSE | RRMSE | Obs | Sim | RMSE | RRMSE | Obs | Sim | RMSE | RRMSE |
| *Phenology* | | | | | | | | | | | | | | | | |
| Emergence [DAP [e]] | 5.8 | 5.4 | 1.1 | 0.19 | 5.2 | 5.4 | 1.2 | 0.23 | 6 | 5.8 | 1.3 | 0.22 | 6 | 5.8 | 1.3 | 0.22 |
| Anthesis [DAP] | 66 | 66 | 2.1 | 0.03 | 65.2 | 64.8 | 2.7 | 0.04 | 64.5 | 65.3 | 2.5 | 0.04 | 64 | 64 | 2.5 | 0.04 |
| Maturity [DAP] | 110.4 | 110.2 | 5.6 | 0.05 | 109.8 | 108.4 | 6.8 | 0.06 | 107.8 | 109.5 | 4.1 | 0.04 | 107.3 | 107.5 | 3 | 0.03 |
| *Morphology* | | | | | | | | | | | | | | | | |
| Number of nodes | 22.8 | 23 | 2.3 | 0.10 | 23.4 | 23.2 | 2.2 | 0.10 | 21.5 | 23.5 | 2.3 | 0.11 | 22.3 | 23.2 | 1 | 0.05 |
| LAI [f] maximum [$m^2$ $m^{-2}$] | 3.3 | 3.6 | 0.6 | 0.19 | 3.2 | 3.3 | 0.6 | 0.20 | 2.9 | 2.4 | 0.5 | 0.17 | 2.8 | 2.2 | 0.6 | 0.22 |
| Canopy height [m] | 1.11 | 1.13 | 0.17 | 0.16 | 1.05 | 1.12 | 0.19 | 0.18 | 1.06 | 1.14 | 0.13 | 0.13 | 1.02 | 1.13 | 0.13 | 0.13 |
| *Biomass & Yield* | | | | | | | | | | | | | | | | |
| Aerial biomass [kg $ha^{-1}$] | 5451 | 4457 | 1173 | 0.22 | 4330 | 4086 | 470 | 0.11 | 4205 | 4940 | 739 | 0.18 | 3903 | 4777 | 949 | 0.24 |
| Harvest index [%] | 0.28 | 0.35 | 0.08 | 0.30 | 0.36 | 0.36 | 0.06 | 0.18 | 0.32 | 0.29 | 0.09 | 0.28 | 0.34 | 0.26 | 0.11 | 0.31 |
| Cotton yield [kg $ha^{-1}$] | 1657 | 1722 | 124 | 0.07 | 1674 | 1568 | 192 | 0.11 | 1390 | 1508 | 395 | 0.28 | 1333 | 1305 | 435 | 0.33 |
| Max ratio of seed cotton mass to boll mass [%] | 72 | 62 | 11 | 0.16 | 71 | 64 | 8 | 0.11 | 66 | 66 | 1 | 0.02 | 62 | 68 | 7 | 0.11 |

a: Observed values. b: simulated by the CSM-CROPGRO-Cotton model. c: root mean square error. d: relative root mean square error. e: days after planting. f: leaf area index.

**Table 5**
Pearson coefficient of correlation between 5 cultivar parameters and the two criteria used for cultivar evaluation (1st quartile (Q1) of $Yield_{opti}$ and Q1 of PW) for each scenario.

| *Parameter* | RCP4.5 | | | | RCP8.5 | | | |
|---|---|---|---|---|---|---|---|---|
| | Q1 of PW | | Q1 of $Yield_{opti}$ | | Q1 of PW | | Q1 of $Yield_{opti}$ | |
| EM-FL | −0.06 | *** | −0.04 | ** | −0.11 | *** | −0.05 | * |
| SD-PM | −0.09 | *** | 0.29 | *** | −0.12 | *** | 0.31 | *** |
| LFMAX | −0.74 | *** | 0.76 | *** | −0.68 | *** | 0.75 | *** |
| SLAVR | −0.11 | *** | 0.26 | *** | −0.07 | *** | 0.28 | *** |
| SIZLF | −0.02 | *ns* | 0.04 | * | −0.01 | *ns* | 0.04 | * |
| Q1 of PW | | | *−0.88* | *** | | | −0.82 | *** |

Symbols ***, **, *, *ns* stand for *P-value* inferior to 0.001, 0.01, 0.05, and superior to 0.05, respectively. Sample size n = 3125. Parameters definition in Table 3.

candidates in total. Their performance was investigated for each replication of 2050 in order to reject those whom $Yield_{opti}$ would drop far below the level of the reference cultivar for some replications of 2050, especially for those where $Yield_{opti}$ was low (Fig. 4).

### 3.2.3. Detailed screening of candidates

The twenty-two candidates VC identified in the first step of discrimination (Fig. 3) and the reference cultivar L484 were plotted on 2D graphics where the GxE interactions were displayed (Fig. 4). In the choice of candidate cultivars, it is important to ensure the absence of failure for the cotton yield in the least productive replications of 2050 (Fig. 4, left columns). A tradeoff exists between the two criteria as the cultivars with the highest gain on yield relative to L484 (top lines) are those with relatively short PW.

For the ten worst replications of 2050 (lowest $Yield_{opti}$ for L484, 10 first left columns in Fig. 4), there was no good candidate for average $Yield_{opti}$ above crop failure yield threshold and long average PW for RCP4.5 (Fig. 4). Those displaying high average $Yield_{opti}$ had a very short average PW and those with long average PW had a low average $Yield_{opti}$ even less than the yield of the reference cultivar L484.

For the ten worst replications, virtual cultivar VC_3121 had the highest average gain on $Yield_{opti}$ and VC_0097 had the highest average gain on PW (Table 6). Virtual VC_3121 consistently had the highest average gain of $Yield_{opti}$ irrespective of conditions and RCP, ranging from 530 to 688 kg $ha^{-1}$ compared to L484. Average gains on $Yield_{opti}$ for VC_0097 were low or slightly negative under the worst conditions. Virtual cultivar VC_0097, always had extra days in the PW compared to L484, up to an average of 11.7 days under the best yield conditions of RCP4.5. In contrast, VC_3121 always had a reduced average number of days in the PW compared to L484, losing up to an average of 15.9 days in the PW compared to L484.

## 4. Discussion

### 4.1. Model calibration and summary observations

The quality of our dataset for model calibration and evaluation was considered to be intermediate to high, according to the usual quality standards (Grassini et al., 2015; Kersebaum et al., 2015). The calibration and evaluation of phenology, growth, and yield were considered sufficient as confirmed by the small RMSE values (Table 4). The genetic parameters for both cultivars (Table 3) were representative of cultivars traits observed in previous studies with smaller and heavier leaves for L484 and higher resilience in drought conditions compared to Allen Commun (Loison, 2015). However, despite 58 years spent between the release of AC and L484 in Cameroon, there has been no improvement in potential photosynthesis (LFMAX, Table 3) consistent with the absence of genetic gain on radiation use efficiency found by Loison et al. (2017).

A similar level of RMSE was found in the literature for cotton phase duration with SUCROS-Cotton (Zhang et al., 2009), LAI maximum and yield using CSM-CROPGRO-Cotton (Ortiz et al., 2009; Thorp et al., 2014b) and EPIC (Ko et al., 2009). We concluded that CSM-CROPGRO-Cotton was properly calibrated and evaluated for our conditions and was therefore suitable for further use.

### 4.2. Cultivars resilience and potential traits

We found no difference in yields between the reference cultivar L484 under RCP4.5, and RCP8.5, despite higher atmospheric $CO_2$ concentration in the latter. This was due to a combination of increase in evapotranspiration due to higher temperatures and a lower amount of rainfall in late season when crop demand for water was high (Appendix B). Gray et al. (2016) also found that drought could offset the positive effect of elevated atmospheric $CO_2$ concentration on peanut yield. The ideotypes described in this study had cotton yields far below the absolute potential fiber yield estimated at 5000 kg $ha^{-1}$ (> 10000 kg $ha^{-1}$ seed cotton yield, Constable and Bange (2015)). Apart from genetic material itself, this was due to the nature of the target environment being highly sub-optimal.

Based on a trade-off between cotton yield and resilience to sub-optimal planting dates, two ideotypes were chosen from the simulation

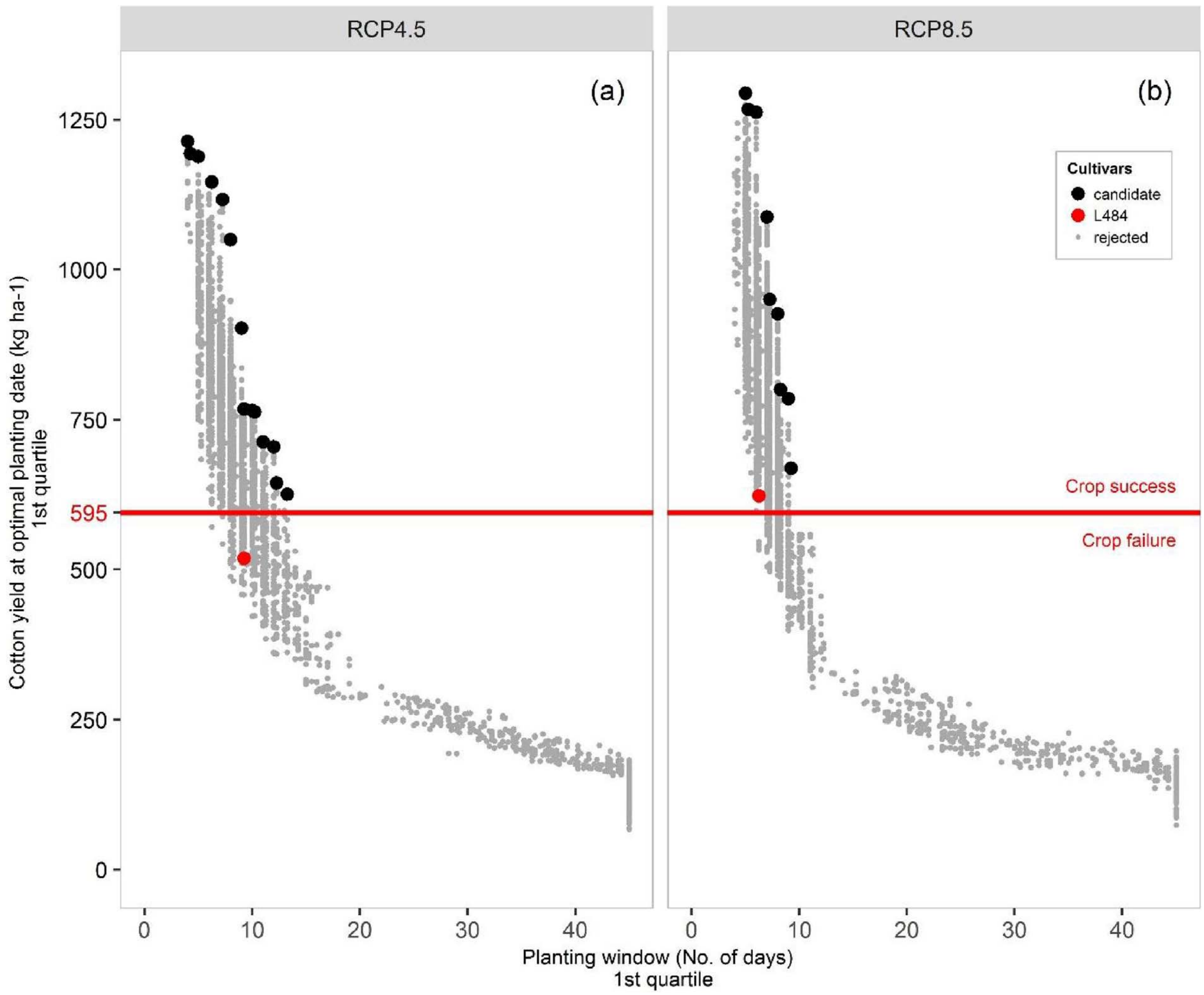


**Fig. 3.** Discrimination of virtual cultivars via multi-objective optimization of 1st quartile (Q1) of cotton yield at optimal planting date ($Yield_{opti}$) and Q1 of planting window (PW) under scenario RCP4.5 (Fig. 3a) and RCP8.5 (Fig. 3b). There are 3126 dots in each panel, with each dot representing a cultivar. The red dot represents the reference cultivar L484. Black dots represent the best virtual cultivars kept for further analysis. Grey dots represent sub-optimal virtual cultivars rejected at this step of analysis. The red line represents the yield threshold of 595 kg $ha^{-1}$ below which crop failure is considered. The Q1 was calculated with a sample size of n = 50. List of candidates from top left to bottom right up to threshold, in RCP4.5: VC_2496, 1866, 3121, 2872, 1722, 2467, 2874, 2068, 2696, 1446, 0743, 0123, 0093 and 0097, and in RCP8.5: VC_3121, 1246, 2996, 2748, 1124, 2963, 2090, 0840 and 2729. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

exercise. The first one was a virtual cultivar achieving yield potential in our target environment (Ideo_Pot) but with very limited resilience to sub-optimal planting date (Appendix A, VC_3121). The second one was a virtual cultivar showing modest or no increase on cotton yield compared to reference, but with better resilience to sub-optimal planting date (Ideo_Sub, Appendix A, VC_0097). Both ideotypes were suitable for the two emissions scenarios.

The two ideotypes shared common characteristics on crop cycle length. Their thermal time requirement for crop cycle length (emergence to boll opening) was highly increased compared to the reference cultivar L484 (+30%, Appendix A). Singh et al. (2014) also found that in West Africa, longer thermal requirement would increase peanut yield under climate change. Luo et al. (2014) estimated a reduction of absolute cotton crop cycle length (emergence to 1st boll) up to 11 days at normal planting date due to increased temperatures found in Australia in 2030. An additional increase in temperatures in 2050, should reduce crop cycle length more than in Luo et al. (2014). Irrespective of the scenarios, at optimal planting date (associated with $Yield_{opti}$), the reference cultivar was found to reach boll opening stage before the end of the rainy season in most occurrences. Boll opening should not happen before the end of the rainy season since cotton could fall on the ground or suffer from bacteria and fungi attacks which affect fiber quality (Buxton et al., 1973), and would make the reference cultivar unsuitable for potential yield achievement (and quality) under future cropping conditions. Both ideotypes require longer reproductive duration. This trait was expected due to the trade-off between early maturity and potential yield in cotton (Bange and Milroy, 2004). However, a genetically modified cotton exhibited early flowering, good fiber quality and enhanced yield, hence breaking former negatives correlations between these traits (Abdurakhmonov et al., 2014). Both ideotypes required early flowering. Sekloka et al. (2008) also found that early flowering onset was a criteria for cotton ideotype under Sub Saharan Africa rainfed conditions.

The two ideotypes also showed significant differences in their physiological traits. For instance, Ideo_Sub had small leaves, small specific leaf area and smaller increase in maximum assimilation rate (LFMAX) compared to Ideo_Pot. Combining reduced leaf area for transpiration and moderate LFMAX, Ideo_Sub prevents drought stress with an avoidance strategy (Tardieu, 2013). On the other hand, Ideo_Pot which had a very large light interception efficiency with big leaves and high assimilation rate (maximum available in the existing range) had a growth maintenance strategy to face drought stress which is likely to increase the risk of crop failure by soil water exhaustion at the end of crop season (Tardieu, 2013). Nevertheless, due to its slightly shorter cycle compared to Ideo_Sub (5 days shorter, Appendix A), Ideo_Pot might be able to prevent late season drought with an escape

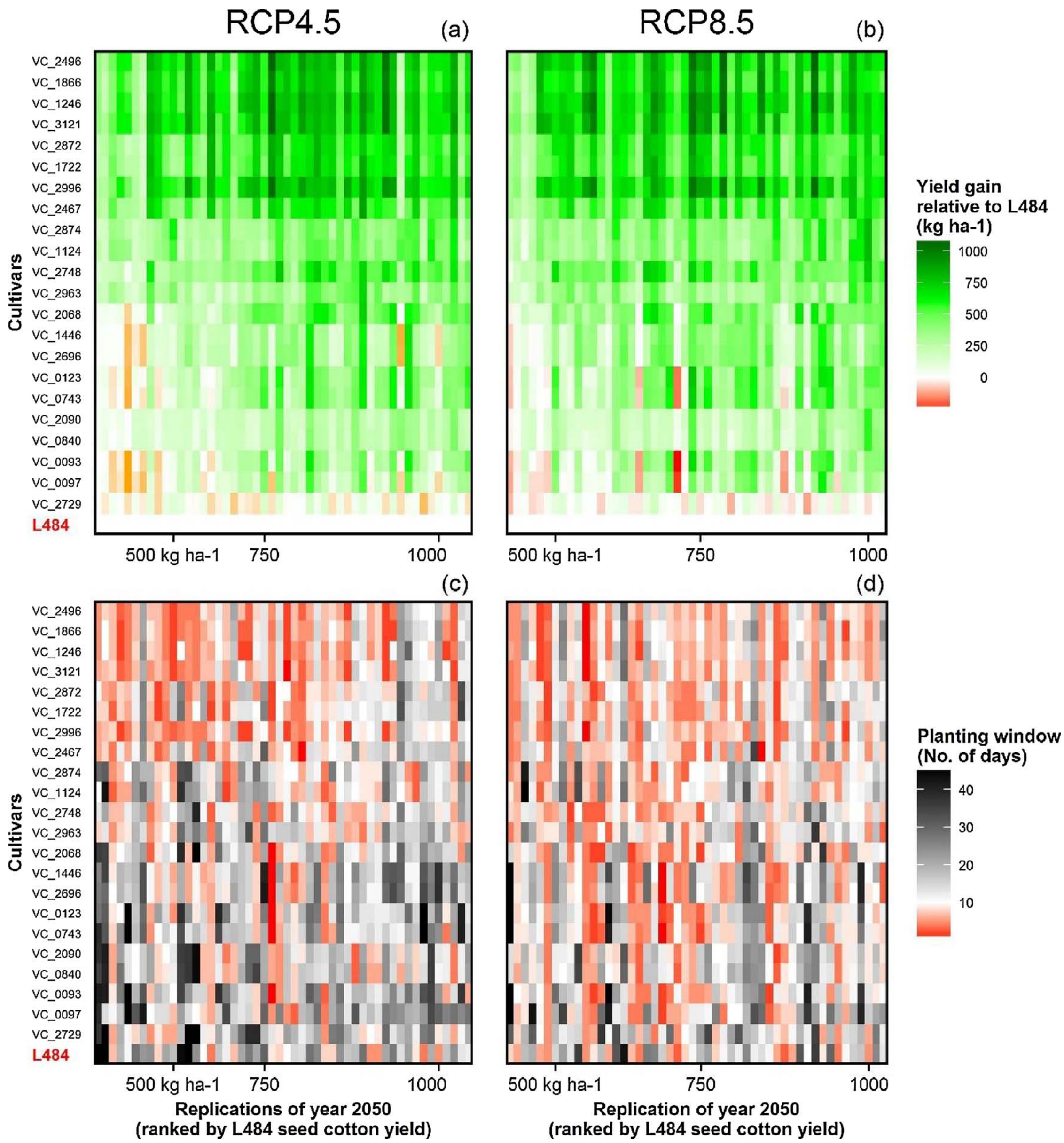


**Fig. 4.** Simulated gain on cotton yield at optimal planting date (Yield$_{opti}$) relative to the reference cultivar L484 (a and b) and absolute planting window (c and d) for 22 virtual cultivars and reference cultivar L484 over 50 replications of climate for year 2050. Panels (a) and (c) are for the emission scenario RCP4.5 while panels (b) and (d) for RCP8.5. For each panel, the lines are ranked from the best (top) to the worst (bottom) cultivar based on the 1st quartile of Yield$_{opti}$. For all panels, the columns are ranked from the worst (left) to the best (right) climate based on Yield$_{opti}$ for the reference cultivar L484. For all panels, the x-axis gives the Yield$_{opti}$ of the reference cultivar L484. For panels (a) and (b), red colors represent yield losses, whole green colors represent yield gains relative to L484. For panels (c) and (d), red colors represents planting windows shorter than 10 days, grey colors represent planting windows longer than 10 days. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

**Table 6**
Expected gains of virtual cultivars compared to reference cultivar L484 on cotton yield for the optimal planting date (Yield$_{opti}$) and planting window (PW) for two emission scenarios (RCP4.5 and RCP8.5) under low or high Yield$_{opti}$ conditions (10 worst or best replications of 2050, respectively). Baselines are average values for cultivar L484.

| RCP | Cultivar | | Low yield conditions | | High yield conditions | |
|---|---|---|---|---|---|---|
| | | | Yield$_{opti}$ (kg ha$^{-1}$) | PW (days) | Yield$_{opti}$ (kg ha$^{-1}$) | PW (days) |
| RCP4.5 | L484 | Baseline | 406 | 23.1 | 1009 | 14.0 |
| | VC_0097 | Gain | −41 | +0.7 | +179 | +11.7 |
| | VC_3121 | Gain | +530 | −15.9 | +633 | −1.2 |
| RCP8.5 | L484 | Baseline | 464 | 14.9 | 962 | 16.6 |
| | VC_0097 | Gain | +58 | +4.8 | +284 | +4.0 |
| | VC_3121 | Gain | +591 | −6.0 | +688 | −6.4 |

strategy (Tardieu, 2013). Both ideotypes had uncorrelated modifications of parameters for specific leaf area (SLA) and LFMAX. This is physiologically possible since SLA is a combination of leaf thickness and leaf density (Garnier et al., 1999). Leaf thickness was found positively correlated with LFMAX (moderate positive correlation, 0.54) but leaf density and LFMAX showed no correlation (grasses, Garnier et al., 1999). Ideo_Pot displaying high LFMAX with big leaves should have thick leaves with low density, while the opposite is expected for Ideo_Sub. The reference cultivar did not have an optimal value for LFMAX. Similarly, Driever et al. (2014) demonstrated that wheat was not bred for potential photosynthetic capacity despite existing genetic variability. All these traits could be screened due to genetic tools already available. For example, genes have already been identified for flowering time and leaf size of barley (Digel et al., 2016), and for cotton, including early flowering (Li et al., 2013), leaf morphology

(Jiang et al., 2000; Song et al., 2005), high photosynthetic rate (Bhatt and Rao, 1980) or even chlorophyll content (Song et al., 2005).

### 4.3. Limitations of the study

We performed an optimization based on a sensitivity analysis of cultivar parameters that affect yield and the crop cycle duration the most in the CSM-CROPGRO-Cotton model (Pathak et al., 2007). In this work, SIZLF and EM-FL were also included in order to obtain a better grasp of plant morphology and phenology. As cotton leaf shape and angles vary among cultivars (Song et al., 2005), further study of the light extinction coefficient should be included in future work. Although the use of multimodel ensembles has become a commonplace for studies (Asseng et al., 2013; Deryng et al., 2016; Martre et al., 2015b), it has been the case once for the design of ideotypes (Tao et al., 2017). Otherwise, the design of ideotypes has only been performed with a single model (Dingkuhn et al., 2015; Gouache et al., 2016; Paleari et al., 2017; Semenov et al., 2014; Stratonovitch and Semenov, 2015; Suriharn et al., 2011), as we have done in this study. We generated virtual cultivars using a grid with existing range of variability on parameter values. Whereas, Singh et al. (2014) created a range of variability around values of parameters from a calibrated cultivar, and Gouache et al. (2016) used existing cultivars previously used in a breeding program. Others studies used evolutionary algorithm to search for the optimal combinations of parameters that maximize yield under future climate (Semenov et al., 2014; Stratonovitch and Semenov, 2015). Despite the use of different methods, all these studies shared the same focus on breeding plant traits rather than calculating exact values of parameters. Contrary to Zheng et al. (2012), this study evaluates genetic variation in yield potential and resilience, hence considering the (strong) impact of soil water and nitrogen limitations on simulations of yields. However, since the research was conducted on research stations, we neglected some of the yield reducing factors (van Ittersum et al., 2003) experienced by farmers in our quest for ideotypes. For example, the impact of weeds on the soil water and nutrient resources available to the crop, while farmer weeding capacity is often found to be sub-optimal since labor is limited. Another limitation is that the planting window (PW) was based on an arbitrary threshold (20% of reference cultivar L484 average yield), similar to Quyen et al. (2015).

There were several limitations in our model as outlined in what follows. Therefore, we suggested that further modelling should be conducted for increased efficiency in ideotype design under low inputs rainfed conditions of Sub Saharan Africa. Firstly, the CSM-CROPGRO-Cotton has not been coupled with genetic models (Ramirez-Villegas et al., 2015; Rötter et al., 2015). However, extensive work has been done previously with the Genegro model based on the CROPGRO-Dry bean model, part of the same family of models (Hoogenboom et al., 2004, 1997; Hoogenboom and White, 2003; White and Hoogenboom, 2003, 1996). Such model, based on physiological and genotypic experimentations are useful for phenotyping and breeding purposes (Pauli et al., 2016) as it grants more biological signification to parameters combinations and facilitates the transition from ideotype (model) to actual cultivars. However, no such gene-based model is available for cotton, there is still a scientific avenue for such modelling. In order to enhance crop model efficiency in ideotype breeding under climate change, (i) high-throughput phenotyping data (field and greenhouse) and crop model should be pipelined to ease the definition of parameter range (Tao et al., 2017) and the correlation between parameters (Semenov and Stratonovitch, 2013), (ii) multi-disciplinary ideotype designing platform should be set up (Rötter et al., 2015), (iii) a better representation of extreme events impact on crop physiology should be integrated (Rötter et al., 2015).

Secondly, the CSM-CROPGRO-Cotton simulates yield quantity, yet cotton is also evaluated for its quality. High cotton yield with poor fiber quality does not optimize economic return. In addition, climate change is expected to also impact on fiber quality (Luo et al., 2016). It is unknown if the ideotypes selected according to our physiological traits will maintain high fiber quality. Therefore, breeders need to carry on with evaluations on fiber quality, taking into account the recommendations in this study, until the successful coupling of the CSM-CROPGRO-Cotton with models of cotton fiber quality. Coupling should be possible since a successful example has been documented for sunflower (Andrianasolo et al., 2014) and some quality models have already been used for cotton (Wang et al., 2014; Zhao et al., 2013, 2012).

### 4.4. Integrating crop model-based physiology into breeding activities

Identified ideotypes had either resilience or yield potential traits. The choice for which one to breed depends on the selected ratio of performance to the level of risk due to sub optimal planting date. However, moving from plant model (ideotype) to plant reality (cultivars) is quite a challenge (Gouache et al., 2016). Nevertheless, the crop model CROPGRO-Peanut has demonstrated a good ability to discriminate cultivars in multi-local trial with a good identification of the five best lines out of the six highest yielding observed in the field and an accurate estimation of lines stability across environment (Banterng et al., 2006). In Cameroon, the integration of model-based physiological traits selection into cotton breeding processes should be implemented as early as the fifth year of the breeding sequence (generation F5) where there are still many different lines (and genetic diversity) but already a population of plants. The use of model for the design of ideotypes could be easily transferred to other crops in Sub Saharan Africa. As a reduced set of observed data enable accurate line ranking and stability across environments (on peanut, Anothai et al. (2009)), the cost of investment to implement such methodology should be small compared to the one regularly observed for breeding programs.

## 5. Conclusion

This study aimed at designing low-input rainfed cotton ideotypes for Northern Cameroon under future climates. We found that: (1) the cultivar that is currently widely grown is likely to be unsuitable under the projected future climate; (2) there was an optimized ideotype for each criteron but none for optimizing both satisfactorily; (3) optimized ideotypes had an earlier anthesis date, a longer reproductive duration, and an increased maximum photosynthetic rate. We recommend that such traits should be considered in the identification of suitable cultivars in breeding programs for future climates. However, further modelling work needs to be done in order to be able to estimate the impact of climate change on fiber quality of such ideotypes. This pioneering work was conducted for a case-study in Northern Cameroon but we feel that the methodology could be expanded to other regions in Sub-Saharan Africa and possibly to new crops.

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## Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.eja.2017.08.003.

## References


Abdurakhmonov, I.Y., Buriev, Z.T., Saha, S., Jenkins, J.N., Abdukarimov, A., Pepper, A.E., 2014. Phytochrome RNAi enhances major fibre quality and agronomic traits of the cotton Gossypium hirsutum L. Nat. Commun. 5. http://dx.doi.org/10.1038/ncomms4062.

Adhikari, P., Ale, S., Bordovsky, J.P., Thorp, K.R., Modala, N.R., Rajan, N., Barnes, E.M., 2016. Simulating future climate change impacts on seed cotton yield in the Texas High Plains using the CSM-CROPGRO-Cotton model. Agric. Water Manag. 164, 317–330. http://dx.doi.org/10.1016/j.agwat.2015.10.011.

Alagarswamy, G., Boote, K.J., Allen, L.H., Jones, J.W., 2006. Evaluating the CROPGRO-soybean model ability to simulate photosynthesis response to carbon dioxide levels. Agron. J. 98, 34. http://dx.doi.org/10.2134/agronj2004-0298.

Amin, A., Nasim, W., Mubeen, M., Nadeem, M., Ali, L., Hammad, H.M., Sultana, S.R., Jabran, K., Rehman, ur, M.H., Ahmad, S., Awais, M., Rasool, A., Fahad, S., Saud, S., Shah, A.N., Ihsan, Z., Ali, S., Bajwa, A.A., Hakeem, K.R., Ameen, A., Amanullah, Rehman, H.U., Alghabar, F., Jatoi, G.H., Akram, M., Khan, A., Islam, F., Ata-Ul-Karim, S.T., Rehmani, M.I.A., Hussain, S., Razaq, M., Fathi, A., 2017. Optimizing the phosphorus use in cotton by using CSM-CROPGRO-cotton model for semi-arid climate of Vehari-Punjab, Pakistan. Environ. Sci. Pollut. Res. 1–13. http://dx.doi.org/10.1007/s11356-016-8311-8.

Anapalli, S., Pettigrew, W., Reddy, K., Ma, L., Fisher, D., Sui, R., 2016. Climate-optimized planting windows for cotton in the lower mississippi delta region. Agronomy 6, 46. http://dx.doi.org/10.3390/agronomy6040046.

Andrianasolo, F.N., Casadebaig, P., Maza, E., Champolivier, L., Maury, P., Debaeke, P., 2014. Prediction of sunflower grain oil concentration as a function of variety, crop management and environment using statistical models. Eur. J. Agron. 54, 84–96. http://dx.doi.org/10.1016/j.eja.2013.12.002.

Anothai, J., Patanothai, A., Pannangpetch, K., Jogloy, S., Boote, K.J., Hoogenboom, G., 2009. Multi-environment evaluation of peanut lines by model simulation with the cultivar coefficients derived from a reduced set of observed field data. Field Crops Res. 110, 111–122. http://dx.doi.org/10.1016/j.fcr.2008.07.009.

Asseng, S., Ewert, F., Rosenzweig, C., Jones, J.W., Hatfield, J.L., Ruane, A.C., Boote, K.J., Thorburn, P.J., Rötter, R.P., Cammarano, D., Brisson, N., Basso, B., Martre, P., Aggarwal, P.K., Angulo, C., Bertuzzi, P., Biernath, C., Challinor, A.J., Doltra, J., Gayler, S., Goldberg, R., Grant, R., Heng, L., Hooker, J., Hunt, L.A., Ingwersen, J., Izaurralde, R.C., Kersebaum, K.C., Müller, C., Naresh Kumar, S., Nendel, C., O'Leary, G., Olesen, J.E., Osborne, T.M., Palosuo, T., Priesack, E., Ripoche, D., Semenov, M.A., Shcherbak, I., Steduto, P., Stöckle, C., Stratonovitch, P., Streck, T., Supit, I., Tao, F., Travasso, M., Waha, K., Wallach, D., White, J.W., Williams, J.R., Wolf, J., 2013. Uncertainty in simulating wheat yields under climate change. Nat. Clim. Change 3, 827–832. http://dx.doi.org/10.1038/nclimate1916.

Bange, M., Milroy, S., 2004. Growth and dry matter partitioning of diverse cotton genotypes. Field Crops Res. 87, 73–87. http://dx.doi.org/10.1016/j.fcr.2003.09.007.

Banterng, P., Patanothai, A., Pannangpetch, K., Jogloy, S., Hoogenboom, G., 2006. Yield stability evaluation of peanut lines: a comparison of an experimental versus a simulation approach. Field Crops Res. 96, 168–175. http://dx.doi.org/10.1016/j.fcr.2005.06.008.

Bassett, T.J., 2014. Capturing the margins: world market prices and cotton farmer incomes in West Africa. World Dev. 59, 408–421. http://dx.doi.org/10.1016/j.worlddev.2014.01.032.

Bhatt, J.G., Rao, M.R.K., 1980. Heterosis in growth and photosynthetic rate in hybrids of cotton. Euphytica 30, 129–133. http://dx.doi.org/10.1007/BF00033668.

Boote, K.J., Jones, J.W., Batchelor, W.D., Nafziger, E.D., Myers, O., 2003. Genetic coefficients in the CROPGRO–Soybean model. Agron. J. 95, 32–51. http://dx.doi.org/10.2134/agronj2003.3200.

Buxton, D.R., Stapleton, H.N., Makki, Y., Briggs, R.E., 1973. Some effects of field weathering of seed cotton in a desert environment1. Agron. J. 65, 14. http://dx.doi.org/10.2134/agronj1973.00021962006500010005x.

Cao, T.-V., Oumarou, P., Gawrysiak, G., Klassou, C., Hau, B., 2011. Short-season cotton (Gossypium hirsutum) may be a suitable response to late planting in sub-Saharan regions. Field Crops Res. 120, 9–20. http://dx.doi.org/10.1016/j.fcr.2010.08.007.

Casadebaig, P., Guilioni, L., Lecoeur, J., Christophe, A., Champolivier, L., Debaeke, P., 2011. SUNFLO, a model to simulate genotype-specific performance of the sunflower crop in contrasting environments. Agric. For. Meteorol. 151, 163–178. http://dx.doi.org/10.1016/j.agrformet.2010.09.012.

Casadebaig, P., Mestries, E., Debaeke, P., 2016. A model-based approach to assist variety evaluation in sunflower crop. Eur. J. Agron. 81, 92–105. http://dx.doi.org/10.1016/j.eja.2016.09.001.

Challinor, A.J., Watson, J., Lobell, D.B., Howden, S.M., Smith, D.R., Chhetri, N., 2014. A meta-analysis of crop yield under climate change and adaptation. Nat. Clim. Change 4, 287–291. http://dx.doi.org/10.1038/nclimate2153.

Constable, G.A., Bange, M.P., 2015. The yield potential of cotton (Gossypium hirsutum L.). Field Crops Res. 182, 98–106. http://dx.doi.org/10.1016/j.fcr.2015.07.017.

Dai, A., 2012. Increasing drought under global warming in observations and models. Nat. Clim. Change 3, 52–58. http://dx.doi.org/10.1038/nclimate1633.

Deryng, D., Elliott, J., Folberth, C., Müller, C., Pugh, T.A.M., Boote, K.J., Conway, D., Ruane, A.C., Gerten, D., Jones, J.W., Khabarov, N., Olin, S., Schaphoff, S., Schmid, E., Yang, H., Rosenzweig, C., 2016. Regional disparities in the beneficial effects of rising CO2 concentrations on crop water productivity. Nat. Clim. Change 6, 786–790. http://dx.doi.org/10.1038/nclimate2995.

Digel, B., Tavakol, E., Verderio, G., Tondelli, A., Xu, X., Cattivelli, L., Rossini, L., von Korff, M., 2016. Photoperiod-H1 (Ppd-H1) controls leaf size. Plant Physiol. 172, 405–415. http://dx.doi.org/10.1104/pp.16.00977.

Dingkuhn, M., Laza, M.R.C., Kumar, U., Mendez, K.S., Collard, B., Jagadish, K., Singh, R.K., Padolina, T., Malabayabas, M., Torres, E., Rebolledo, M.C., Manneh, B., Sow, A., 2015. Improving yield potential of tropical rice: achieved levels and perspectives through improved ideotypes. Field Crops Res. 182, 43–59. http://dx.doi.org/10.1016/j.fcr.2015.05.025.

Driever, S.M., Lawson, T., Andralojc, P.J., Raines, C.A., Parry, M.A.J., 2014. Natural variation in photosynthetic capacity, growth, and yield in 64 field-grown wheat genotypes. J. Exp. Bot. 65, 4959–4973. http://dx.doi.org/10.1093/jxb/eru253.

Dzotsi, K.A., Basso, B., Jones, J.W., 2013. Development, uncertainty and sensitivity analysis of the simple SALUS crop model in DSSAT. Ecol. Modell. 260, 62–76. http://dx.doi.org/10.1016/j.ecolmodel.2013.03.017.

Gérardeaux, E., Sultan, B., Palaï, O., Guiziou, C., Oettli, P., Naudin, K., 2013. Positive effect of climate change on cotton in 2050 by CO2 enrichment and conservation agriculture in Cameroon. Agron. Sustain. Dev. 33, 485–495. http://dx.doi.org/10.1007/s13593-012-0119-4.

García-Vila, M., Fereres, E., 2012. Combining the simulation crop model AquaCrop with an economic model for the optimization of irrigation management at farm level. Eur. J. Agron. 36, 21–31. http://dx.doi.org/10.1016/j.eja.2011.08.003.

Garnier, E., Salager, J.-L., Laurent, G., Sonie, L., 1999. Relationships between photosynthesis, nitrogen and leaf structure in 14 grass species and their dependence on the basis of expression. New Phytol. 143, 119–129. http://dx.doi.org/10.1046/j.1469-8137.1999.00426.x.

Gijsman, A.J., Hoogenboom, G., Parton, W.J., Kerridge, P.C., 2002. Modifying DSSAT crop models for low-input agricultural systems using a soil organic matter-residue module from CENTURY. Agron. J. 94, 462. http://dx.doi.org/10.2134/agronj2002.4620.

Godwin, D.C., Singh, U., 1998. Nitrogen balance and crop response to nitrogen in upland and lowland cropping systems. In: Tsuji, G., Hoogenboom, G., Thornton, P. (Eds.), Understanding Options for Agricultural Production SE – 4, Systems Approaches for Sustainable Agricultural Development. Springer, Netherlands, pp. 55–77. http://dx.doi.org/10.1007/978-94-017-3624-4_4.

Gouache, D., Bogard, M., Pegard, M., Thepot, S., Garcia, C., Hourcade, D., Paux, E., Oury, F.-X., Rousset, M., Deswarte, J.-C., Le Bris, X., 2016. Bridging the gap between ideotype and genotype: challenges and prospects for modelling as exemplified by the case of adapting wheat (Triticum aestivum L.) phenology to climate change in France. Field Crops Res. http://dx.doi.org/10.1016/j.fcr.2015.12.012.

Grassini, P., van Bussel, L.G.J., Van Wart, J., Wolf, J., Claessens, L., Yang, H., Boogaard, H., de Groot, H., van Ittersum, M.K., Cassman, K.G., 2015. How good is good enough? data requirements for reliable crop yield simulations and yield-gap analysis. Field Crops Res. 177, 49–63. http://dx.doi.org/10.1016/j.fcr.2015.03.004.

Gray, S.B., Dermody, O., Klein, S.P., Locke, A.M., McGrath, J.M., Paul, R.E., Rosenthal, D.M., Ruiz-Vera, U.M., Siebers, M.H., Strellner, R., Ainsworth, E.A., Bernacchi, C.J., Long, S.P., Ort, D.R., Leakey, A.D.B., 2016. Intensifying drought eliminates the expected benefits of elevated carbon dioxide for soybean. Nat. Plants 2, 16132. http://dx.doi.org/10.1038/nplants.2016.132.

Guan, K., Sultan, B., Biasutti, M., Baron, C., Lobell, D.B., 2017. Assessing climate adaptation options and uncertainties for cereal systems in West Africa. Agric. For. Meteorol. 232, 291–305. http://dx.doi.org/10.1016/j.agrformet.2016.07.021.

He, L., Asseng, S., Zhao, G., Wu, D., Yang, X., Zhuang, W., Jin, N., Yu, Q., 2015. Impacts of recent climate warming, cultivar changes, and crop management on winter wheat phenology across the Loess Plateau of China. Agric. For. Meteorol. 200, 135–143. http://dx.doi.org/10.1016/j.agrformet.2014.09.011.

Hoogenboom, G., White, J.W., 2003. Improving physiological assumptions of simulation models by using gene-based approaches. Agron. J. 95, 82–89. http://dx.doi.org/10.2134/AGRONJ2003.8200.

Hoogenboom, G., White, J.W., Acosta-Gallegos, J., Gaudiel, R.G., Myers, J.R., Silbernagel, M.J., 1997. Evaluation of a crop simulation model that incorporates gene action. Agron. J. 89, 613. http://dx.doi.org/10.2134/agronj1997.00021962008900040013x.

Hoogenboom, G., White, J.W., Messina, C.D., 2004. From genome to crop: integration through simulation modeling. Field Crops Res. 90, 145–163. http://dx.doi.org/10.1016/j.fcr.2004.07.014.

Hoogenboom, G., Jones, J.W., Wilkens, P.W., Porter, C.H., Boote, K.J., Hunt, L.A., Singh, U., Lizaso, J.I., White, J.W., Uryasev, O., Ogoshi, R., Koo, J., Shelia, V., Tsuji, G.Y., 2015. Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.6. DSSAT Foundation, Prosser, Washington. http://dssat.net.

ICAC, 2017. 100 facts about cotton. Accessed online at icac.org/tech/Overview/100-facts-about-cotton on 2017-02-22. [WWW Document]. URL https://www.icac.org/tech/Overview/100-facts-about-cotton. (Accessed 22 February 2017).

Jeuffroy, M.-H., Casadebaig, P., Debaeke, P., Loyce, C., Meynard, J.-M., 2014. Agronomic model uses to predict cultivar performance in various environments and cropping systems. A review. Agron. Sustain. Dev. 34, 121–137. http://dx.doi.org/10.1007/s13593-013-0170-9.

Jiang, C., Wright, R.J., Woo, S.S., DelMonte, T.A., Paterson, A.H., 2000. QTL analysis of leaf morphology in tetraploid Gossypium (cotton). TAG Theor. Appl. Genet. 100, 409–418. http://dx.doi.org/10.1007/s001220050054.

Jones, P.G., Thornton, P.K., 2000. MarkSim. Agron. J. 92, 445. http://dx.doi.org/10.2134/agronj2000.923445x.

Jones, J.W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P., Singh, U., Gijsman, A.J., Ritchie, J., 2003. The DSSAT cropping system model. Eur. J. Agron. 18, 235–265. http://dx.doi.org/10.1016/S1161-0301(02)00107-7.

Kersebaum, K.C., Boote, K.J., Jorgenson, J.S., Nendel, C., Bindi, M., Frühauf, C., Gaiser, T., Hoogenboom, G., Kollas, C., Olesen, J.E., Rötter, R.P., Ruget, F., Thorburn, P.J., Trnka, M., Wegehenkel, M., 2015. Analysis and classification of data sets for calibration and validation of agro-ecosystem models. Environ. Model. Softw. 72, 402–417. http://dx.doi.org/10.1016/j.envsoft.2015.05.009.

Kim, H.-Y., Ko, J., Kang, S., Tenhunen, J., 2013. Impacts of climate change on paddy rice yield in a temperate climate. Glob. Change Biol. 19, 548–562. http://dx.doi.org/10.1111/gcb.12047.
Ko, J., Piccinni, G., Guo, W., Steglich, E., 2009. Parameterization of EPIC crop model for simulation of cotton growth in South Texas. J. Agric. Sci. 147, 169. http://dx.doi.org/10.1017/S0021859608008356.
Li, C., Wang, X., Dong, N., Zhao, H., Xia, Z., Wang, R., Converse, R.L., Wang, Q., 2013. QTL analysis for early-maturing traits in cotton using two upland cotton (Gossypium hirsutum L.) crosses. Breed. Sci. 63, 154–563. http://dx.doi.org/10.1270/jsbbs.63.154.
Loison, R., Audebert, A., Chopart, J., Debaeke, P., Dessauw, D., Gourlot, J., Gozé, E., Jean, J., Gérardeaux, E., 2017. Sixty years of breeding in Cameroon improved fibre but not seed cotton yield. Exp. Agric. 53, 202–209. http://dx.doi.org/10.1017/S0014479716000302.
Loison, R., 2015. Ecophysiological Analysis and Modeling of Genotype by Environment by Crop Management Interactions on Cotton (Gossypium hirsutum L.) in Cameroon for the Design of Ideotypes. Université de Montpellier (English. < tel-01262261 >).
Luo, Q., Bange, M., Clancy, L., 2014. Cotton crop phenology in a new temperature regime. Ecol. Modell. 285, 22–29. http://dx.doi.org/10.1016/j.ecolmodel.2014.04.018.
Luo, Q., Bange, M., Johnston, D., 2016. Environment and cotton fibre quality. Clim. Change 138, 207–221. http://dx.doi.org/10.1007/s10584-016-1715-0.
M'Biandoun, M., Olina, J., 2006. Pluviosité en région soudano-sahélienne au Nord du Cameroun: conséquences sur l'agriculture. Agron. Africaine 18, 95–104. http://dx.doi.org/10.4314/aga.v18i2.1683.
Mahop, F., Van Ranst, E., 1997. CoÛt de l'épuisement du sol en zone cotonnière camerounaise: impact sur l'environnement. Tropicultura 15, 203–208.
Martre, P., Quilot-Turion, B., Luquet, D., Memmah, M.-M.O.-S., Chenu, K., Debaeke, P., 2015a. Model-assisted phenotyping and ideotype design. In: Calderini, D., Sadras, V. (Eds.), Crop Physiology. Alications for Genetic Improvement and Agronomy. Elsevier, pp. 349–373. http://dx.doi.org/10.1016/B978-0-12-417104-6.00014-5.
Martre, P., Wallach, D., Asseng, S., Ewert, F., Jones, J.W., Rötter, R.P., Boote, K.J., Ruane, A.C., Thorburn, P.J., Cammarano, D., Hatfield, J.L., Rosenzweig, C., Aggarwal, P.K., Angulo, C., Basso, B., Bertuzzi, P., Biernath, C., Brisson, N., Challinor, A.J., Doltra, J., Gayler, S., Goldberg, R., Grant, R.F., Heng, L., Hooker, J., Hunt, L.A., Ingwersen, J., Izaurralde, R.C., Kersebaum, K.C., Müller, C., Kumar, S.N., Nendel, C., O'leary, G., Olesen, J.E., Osborne, T.M., Palosuo, T., Priesack, E., Ripoche, D., Semenov, M.A., Shcherbak, I., Steduto, P., Stöckle, C.O., Stratonovitch, P., Streck, T., Supit, I., Tao, F., Travasso, M., Waha, K., White, J.W., Wolf, J., 2015b. Multimodel ensembles of wheat growth: many models are better than one. Glob. Change Biol. 21, 911–925. http://dx.doi.org/10.1111/gcb.12768.
Meinshausen, M., Smith, S.J., Calvin, K., Daniel, J.S., Kainuma, M.L.T., Lamarque, J.-F., Matsumoto, K., Montzka, S.A., Raper, S.C.B., Riahi, K., Thomson, A., Velders, G.J.M., van Vuuren, D.P.P., 2011. The RCP greenhouse gas concentrations and their extensions from 1765 to 2300. Clim. Change 109, 213–241. http://dx.doi.org/10.1007/s10584-011-0156-z.
Naudin, K., Gozé, E., Balarabe, O., Giller, K.E., Scopel, E., 2010. Impact of no tillage and mulching practices on cotton production in North Cameroon: a multi-locational on-farm assessment. Soil Tillage Res. 108, 68–76. http://dx.doi.org/10.1016/j.still.2010.03.002.
Ortiz, B.V., Hoogenboom, G., Vellidis, G., Boote, K.J., Davis, R.F., Perry, C.D., 2009. Aadapting the cropgro-cotton model to simulate cotton biomass and yield under southern root-knot nematode parasitism. Trans. ASABE 52, 2129–2140.
Paleari, L., Movedi, E., Cappelli, G., Wilson, L.T., Confalonieri, R., 2017. Surfing parameter hyperspaces under climate change scenarios to design future rice ideotypes. Glob. Change Biol. http://dx.doi.org/10.1111/gcb.13682.
Pathak, T.B., Fraisse, C.W., Jones, J.W., Messina, C.D., Hoogenboom, G., 2007. Use of global sensitivity analysis for cropgro cotton model development. Trans. ASABE 50, 2295–2302.
Pathak, T.B., Jones, J.W., Fraisse, C.W., Wright, D., Hoogenboom, G., 2012. Uncertainty analysis and parameter estimation for the CSM-CROPGRO-cotton model. Agron. J. 104, 1363–1373. http://dx.doi.org/10.2134/agronj2011.0349.
Pauli, D., Chapman, S.C., Bart, R., Topp, C.N., Lawrence-Dill, C.J., Poland, J., Gore, M.A., 2016. The quest for understanding phenotypic variation via integrated approaches in the field environment. Plant Physiol.. http://dx.doi.org/10.1104/pp.16.00592. pp. 00592.2016.
Peltzer, R., Röttger, D., 2013. Cotton Sector Organisation Models and Their Impact on Farmer's Productivity and Income. Bonn.
Quilot-Turion, B., Ould-Sidi, M.-M., Kadrani, A., Hilgert, N., Génard, M., Lescourret, F., 2012. Optimization of parameters of the Virtual Fruit model to design peach genotype for sustainable production systems. Eur. J. Agron. 42, 34–48. http://dx.doi.org/10.1016/j.eja.2011.11.008.
Quyen, L.N., Affholder, F., Montagne, J., Jourdain, D., Ripoche, A., Capillon, A., 2015. Sowing windows for a spring crop introduced in rice cultivation areas affected by low temperature and radiation. Exp. Agric. 51, 540–566. http://dx.doi.org/10.1017/S0014479714000465.
R Core Team, 2017. R: A Language and Environment for Statistical Computing.
Rötter, R.P., Höhn, J., Trnka, M., Fronzek, S., Carter, T.R., Kahiluoto, H., 2013. Modelling shifts in agroclimate and crop cultivar response under climate change. Ecol. Evol. 3, 4197–4214. http://dx.doi.org/10.1002/ece3.782.
Rötter, R.P., Tao, F., Höhn, J.G., Palosuo, T., 2015. Use of crop simulation modelling to aid ideotype design of future cereal cultivars. J. Exp. Bot. 66, 3463–3476. http://dx.doi.org/10.1093/jxb/erv098.
Ramirez-Villegas, J., Watson, J., Challinor, A.J., 2015. Identifying traits for genotypic adaptation using crop models. J. Exp. Bot. 66, 3451–3462. http://dx.doi.org/10.1093/jxb/erv014.
Reynolds, M., Langridge, P., 2016. Physiological breeding. Curr. Opin. Plant Biol. 31, 162–171. http://dx.doi.org/10.1016/j.pbi.2016.04.005.
Rezaei, E.E., Gaiser, T., Siebert, S., Sultan, B., Ewert, F., 2014. Combined impacts of climate and nutrient fertilization on yields of pearl millet in Niger. Eur. J. Agron. 55, 77–88. http://dx.doi.org/10.1016/j.eja.2014.02.001.
Riahi, K., Rao, S., Krey, V., Cho, C., Chirkov, V., Fischer, G., Kindermann, G., Nakicenovic, N., Rafaj, P., 2011. RCP 8.5—a scenario of comparatively high greenhouse gas emissions. Clim. Change 109, 33–57. http://dx.doi.org/10.1007/s10584-011-0149-y.
Ripoche, A., Crétenet, M., Corbeels, M., Affholder, F., Naudin, K., Sissoko, F., Douzet, J.-M., Tittonell, P., 2015. Cotton as an entry point for soil fertility maintenance and food crop productivity in savannah agroecosystems-Evidence from a long-term experiment in southern Mali. Field Crops Res. 177, 37–48. http://dx.doi.org/10.1016/j.fcr.2015.02.013.
Ritchie, J.T., 1998. Soil water balance and plant water stress. In: Tsuji, G., Hoogenboom, G., Thornton, P. (Eds.), Understanding Options for Agricultural Production SE − 3, Systems Approaches for Sustainable Agricultural Development. Springer, Netherlands, pp. 41–54. http://dx.doi.org/10.1007/978-94-017-3624-4_3.
Sekloka, E., Lançon, J., Gozé, E., Hau, B., Lewicki-Dhainaut, S., Thomas, G., 2008. Breeding new cotton varieties to fit the diversity of cropping conditions in africa: effect of plant architecture, earliness and effective flowering time on late-planted cotton productivity. Exp. Agric. 44, 197–207. http://dx.doi.org/10.1017/S0014479708006157.
Semenov, M.A., Stratonovitch, P., 2013. Designing high-yielding wheat ideotypes for a changing climate. Food Energy Secur. 2, 185–196. http://dx.doi.org/10.1002/fes3.34.
Semenov, M.A., Stratonovitch, P., Alghabari, F., Gooding, M.J., 2014. Adapting wheat in Europe for climate change. J. Cereal Sci. 59, 245–256. http://dx.doi.org/10.1016/j.jcs.2014.01.006.
Singh, P., Boote, K.J., Kumar, U., Srinivas, K., Nigam, S.N., Jones, J.W., 2012. Evaluation of genetic traits for improving productivity and adaptation of groundnut to climate change in India. J. Agron. Crop Sci. 198, 399–413. http://dx.doi.org/10.1111/j.1439-037X.2012.00522.x.
Singh, P., Nedumaran, S., Ntare, B.R., Boote, K.J., Singh, N.P., Srinivas, K., Bantilan, M.C.S., 2014. Potential benefits of drought and heat tolerance in groundnut for adaptation to climate change in India and West Africa. Mitig. Adapt. Strategies Glob. Change 19, 509–529. http://dx.doi.org/10.1007/s11027-012-9446-7.
Soler, C.M.T., Maman, N., Zhang, X., Mason, S.C., Hoogenboom, G., 2008. Determining optimum planting dates for pearl millet for two contrasting environments using a modelling approach. J. Agric. Sci. 146, 445–459. http://dx.doi.org/10.1017/S0021859607007617.
Song, X.-L., Guo, W.-Z., Han, Z.-G., Zhang, T.-Z., 2005. Quantitative trait loci mapping of leaf morphological traits and chlorophyll content in cultivated tetraploid cotton. J. Integr. Plant Biol. 47, 1382–1390. http://dx.doi.org/10.1111/j.1744-7909.2005.00172.x.
Stratonovitch, P., Semenov, M.A., 2015. Heat tolerance around flowering in wheat identified as a key trait for increased yield potential in Europe under climate change. J. Exp. Bot. 66, 3599–3609. http://dx.doi.org/10.1093/jxb/erv070.
Sultan, B., Bella-Medjo, M., Berg, A., Quirion, P., Janicot, S., 2010. Multi-scales and multi-sites analyses of the role of rainfall in cotton yields in West Africa. Int. J. Climatol. 30, 58–71. http://dx.doi.org/10.1002/joc.1872.
Suriharn, B., Patanothai, A., Boote, K.J., Hoogenboom, G., 2011. Designing a peanut ideotype for a target environment using the CSM-CROPGRO-Peanut Model. Crop Sci. 51, 1887. http://dx.doi.org/10.2135/cropsci2010.08.0457.
Tao, F., Rötter, R.P., Palosuo, T., Díaz-Ambrona, C.G.H., Mínguez, M.I., Semenov, M.A., Kersebaum, K.C., Nendel, C., Cammarano, D., Hoffmann, H., Ewert, F., Dambreville, A., Martre, P., Rodríguez, L., Ruiz-Ramos, M., Gaiser, T., Höhn, J.G., Salo, T., Ferrise, R., Bindi, M., Schulman, A.H., 2017. Designing future barley ideotypes using a crop model ensemble. Eur. J. Agron. 82, 144–162. http://dx.doi.org/10.1016/j.eja.2016.10.012.
Tardieu, F., 2013. Plant response to environmental conditions: assessing potential production, water demand, and negative effects of water deficit. Front. Physiol. 4, 17. http://dx.doi.org/10.3389/fphys.2013.00017.
Thomson, A.M., Calvin, K.V., Smith, S.J., Kyle, G.P., Volke, A., Patel, P., Delgado-Arias, S., Bond-Lamberty, B., Wise, M.A., Clarke, L.E., Edmonds, J.A., 2011. RCP4.5: a pathway for stabilization of radiative forcing by 2100. Clim. Change 109, 77–94. http://dx.doi.org/10.1007/s10584-011-0151-4.
Thornton, P.K., Jones, P.G., Ericksen, P.J., Challinor, A.J., 2010. Agriculture and food systems in sub-Saharan Africa in a 4 °C+ world. Philos. Trans. R. Soc. Lond. A Math. Phys. Eng. Sci. 369.
Thorp, K.R., Ale, S., Bange, M.P., Barnes, E.M., Hoogenboom, G., Lascano, R.J., McCarthy, A.C., Nair, S., Paz, J.O., Rajan, N., Reddy, K.R., Wall, G.W., White, J.W., 2014a. Development and application of process-based simulation models for cotton production: a review of past, present, and future directions. J. Cotton Sci. 18, 10–47.
Thorp, K.R., Barnes, E.M., Hunsaker, D.J., Kimball, B.A., White, J.W., Nazareth, V.J., Hoogenboom, G., 2014b. Evaluation of CSM-CROPGRO-Cotton for simulating effects of management and climate change on cotton growth and evapotranspiration in an arid environment. Trans. ASABE 57, 1627–1642. http://dx.doi.org/10.13031/trans.57.10612.
Tschirley, D.L., David, L., Poulton, C., Labaste, P., 2009. Organization and Performance of Cotton Sectors in Africa. The World Bankhttp://dx.doi.org/10.1596/978-0-8213-7770-3.
Wajid, A., Ahmad, A., Hussain, M., Rahman, M.H.U., Khaliq, T., Mubeen, M., Rasul, F., Bashir, U., Awais, M., Iqbal, J., Sultana, S.R., Hoogenboom, G., 2014. Modeling growth: development and seed-cotton yield for varying nitrogen increments and planting dates using DSSAT. Pak. J. Agric. Sci. 51, 639–647.
Wang, X., Zhang, L., Evers, J.B., Mao, L., Wei, S., Pan, X., Zhao, X., van der Werf, W., Li, Z., 2014. Predicting the effects of environment and management on cotton fibre

growth and quality: a functional-structural plant modelling approach. AoB Plants 6, plu040. http://dx.doi.org/10.1093/aobpla/plu040.
White, J.W., Hoogenboom, G., 1996. Simulating effects of genes for physiological traits in a process-oriented crop model. Agron. J. 88, 416. http://dx.doi.org/10.2134/agronj1996.00021962008800030009x.
White, J.W., Hoogenboom, G., 2003. Gene-Based approaches to crop simulation. Agron. J. 95, 52–64. http://dx.doi.org/10.2134/AGRONJ2003.5200.
World Bank, 2016. CMO Historical Data Annual. Available online at http://pubdocs.worldbank.org/en/547711449679682156/CMO-Historical-Data-Annual.xlsx. (Accessed 5 September 2016) [WWW Document]. URL http://pubdocs.worldbank.org/en/547711449679682156/CMO-Historical-Data-Annual.xlsx. (Accessed 9 May 2016).
World Bank, 2017. Commodity Markets. Price forecasts. April 2017 [WWW Document]. URL http://www.worldbank.org/en/research/commodity-markets . (Accessed 19 July 2017).
Xiao, D., Tao, F., 2014. Contributions of cultivars, management and climate change to winter wheat yield in the North China Plain in the past three decades. Eur. J. Agron. 52, 112–122. http://dx.doi.org/10.1016/j.eja.2013.09.020.
Yang, Y., Yang, Y., Han, S., Macadam, I., Liu, D.L., 2014. Prediction of cotton yield and water demand under climate change and future adaptation measures. Agric. Water Manag. 144, 42–53. http://dx.doi.org/10.1016/j.agwat.2014.06.001.
Zhang, L., Werf, W. van der, Cao, W., Li, B., Pan, X., Spiertz, J.H., 2009. 2009. Development and validation of SUCROS-Cotton: a potential crop growth simulation model for cotton. NJAS wageningen. J. Life Sci.
Zhao, W., Meng, Y., Li, W., Chen, B., Xu, N., Wang, Y., Zhou, Z., Oosterhuis, D.M., 2012. A model for cotton (Gossypium hirsutum L.) fiber length and strength formation considering temperature-radiation and N nutrient effects. Ecol. Modell. 243, 112–122. http://dx.doi.org/10.1016/j.ecolmodel.2012.06.015.
Zhao, W., Zhou, Z., Meng, Y., Chen, B., Wang, Y., 2013. Modeling fiber fineness, maturity, and micronaire in cotton (Gossypium hirsutum L.). J. Integr. Agric. 12, 67–79. http://dx.doi.org/10.1016/S2095-3119(13)60206-3.
Zheng, B., Chenu, K., Fernanda Dreccer, M., Chapman, S.C., 2012. Breeding for the future: what are the potential impacts of future frost and heat events on sowing and flowering time requirements for Australian bread wheat (Triticum aestivium) varieties? Glob. Change Biol. 18, 2899–2914. http://dx.doi.org/10.1111/j.1365-2486.2012.02724.x.
Zheng, B., Chenu, K., Chapman, S.C., 2016. Velocity of temperature and flowering time in wheat − assisting breeders to keep pace with climate change. Glob. Change Biol. 22, 921–933. http://dx.doi.org/10.1111/gcb.13118.
van Ittersum, M., Leffelaar, P., van Keulen, H., Kropff, M., Bastiaans, L., Goudriaan, J., 2003. On approaches and applications of the Wageningen crop models. Eur. J. Agron. 18, 201–234. http://dx.doi.org/10.1016/S1161-0301(02)00106-5.