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Modelling Bambara groundnut yield in Southern Africa: towards a climate-resilient future

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ABSTRACT: Current agriculture depends on a few major species grown as monocultures that are supported by global research underpinning current productivity. However, many hundreds of alternative crops have the potential to meet real world challenges by sustaining humanity, diversifying agricultural systems for food and nutritional security, and especially responding to climate change through their resilience to certain climate conditions. Bambara groundnut (*Vigna subterranea* (L.) Verdc.), an underutilised African legume, is an exemplar crop for climate resilience. Predicted yield performances of Bambara groundnut by AquaCrop (a crop–water productivity model) were evaluated for baseline (1980–2009) and mid-century climates (2040–2069) under 20 downscaled Global Climate Models (CMIP5-RCP8.5), as well as for climate sensitivities (AgMIP-C3MP) across 3 locations in Southern Africa (Botswana, South Africa, Namibia). Different landraces of Bambara groundnut originating from various semi-arid African locations showed diverse yield performances with diverse sensitivities to climate. S19 originating from hot-dry conditions in Namibia has greater future yield potential compared to the Swaziland landrace Uniswa Red-UN across study sites. South Africa has the lowest yield under the current climate, indicating positive future yield trends. Namibia reported the highest baseline yield at optimum current temperatures, indicating less yield potential in future climates. Bambara groundnut shows positive yield potential at temperatures of up to ~31°C, with further warming pushing yields down. Thus, many regions in Southern Africa can utilize Bambara groundnut successfully in the coming decades. This modelling exercise supports decisions on genotypic suitability for present and future climates at specific locations.

KEY WORDS: Bambara groundnut · Southern Africa · Future scenarios · Climate sensitivities

1. INTRODUCTION

Intensified agricultural systems have reported the constant reliance on only 30 major crops to meet the global food demand (FAO 1996). However, ~7000 species have been extensively harvested for food around the world (Wilson 1992). These alternative, or so called 'underutilised' crops, have the potential to meet the challenges in the developing world, providing agricultural diversification, dietary diversification and climate resilience. The major crops have significant global land coverage, marketing systems and well-developed commercial research, and are currently receiving maximum research attention. Their advocates have access to a recognised body of quantitative evidence based on structured national and international research that span disciplines from plant breeding to marketing and policy studies. In contrast, underutilised crops have no such support systems, relying only on fragmentary knowledge and often qualitative local evidence from growers rather than multi-locational research that spans the whole supply chain. Perhaps, the most successful development of an underutilised crop to date is that of cow-

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pea (*Vigna unguiculata* L.), primarily through the work of the International Institute of Tropical Agriculture (2009) which is mandated to do research on this crop. Bambara groundnut is a complementary crop to cowpea and generally commands a premium in countries where it is traditionally grown, particularly in sub-Saharan Africa (Linnemann & Azam-Ali 1993). Over the past 3 decades, a series of EU projects from the Sutton Bonington Campus of the University of Nottingham (UK) has developed a strong research program for Bambara groundnut that is hosted within the Crops For the Future (CFF; www.cffresearch.org) research framework linking various disciplinary groups working on Bambara groundnut — the BamNetwork (http://bambaragroundnut.org/).

Bambara groundnut is an underutilised African legume with a centre of origin in the region around Cameroon. Surveys in this area have identified the most likely ancestor to be *V. subterranea* var. *spontanea* (Doku & Karikari 1971) and this relationship has been confirmed through isozyme and other molecular analyses (Pasquet et al. 1999, Amadou et al. 2001, Massawe et al. 2002, Massawe et al. 2004, Ntundu et al. 2004). The cultivated crop exists as landraces, and is grown extensively in sub-Saharan Africa. A landrace is a locally adapted strain of a species that has been selected through traditional methods, and is not influenced by modern breeding technologies. Bambara groundnut is grown throughout Africa, from Senegal across to Kenya and from the Sahara to South Africa, and was expanded over southeast Asia (Indonesia). Traditionally, it is grown by women farmers as an intercrop in subsistence farming systems on poor soils in hot climates, generally in regions where the cultivation of other legumes (e.g. groundnut *Arachis hypogea*) is too risky because of the threat of drought (Doku & Karikari 1971, Ezueh 1977, Haque 1980, Linnemann 1990, Doku 1996). Bambara groundnut has been identified as a drought-tolerant crop that can produce some yield where other crops (e.g. groundnut) fail (Harris & Azam-Ali 1993). Two landraces — S19-3 (Namibia) and Uniswa Red-UN (Swaziland) — have been commonly used for various studies on physiology, agronomy, molecular genetics, modelling and mapping at Nottingham (Bannayan 2001, Mwale et al. 2007, Karunaratne et al. 2010, Karunaratne et al. 2011b). Furthermore, the climate-resilient features of these 2 landraces have been extensively examined in several physiology studies (Harris & Azam-Ali 1993, Mwale et al. 2007), providing data specifically on temperature and water stress coefficients for model improvements (Karunaratne et al. 2011b) and calibration of existing models (Karunaratne et al. 2011a). A parallel modelling exercise was conducted at the University of Nottingham, evaluating adaptation strategies for climate change in Cameroon under scenario GISS A2 (Goddard Institute for Space Studies A2) for 2080. The results reported that a 14.6% reduction in maize yield was converted to a 32.1% increase, a 39.9% decrease in sorghum yield was converted to a 17.6% increase, while a 12.9% decrease in Bambara groundnut yield was converted to a 3-fold increase (37.1%) by altering the sowing date to increase the length of the growing period, together with higher CO_2 concentrations.

Climate change is one of the primary concerns for humanity in the 21st century. The IPCC Fifth Assessment Report concludes that there is strong evidence that human activities have influenced the world's climate over the last century and a half (IPCC 2014). Changes to the global climate, notably to regional spatial and temporal temperature patterns due to increased atmospheric concentrations of greenhouse gases (GHGs) are predicted to have important consequences for crop production (Parry et al. 2004, Porter et al. 2014, Rosenzweig et al. 2014). A relative decline in maize and soybean yield of ~17% occurred per 1°C rise in the growing-season temperature in the USA from 1982 to 1998 (Lobell & Asner 2003), whereas rice grain yield declined by ~10% in the Philippines from 1992 to 2003 (Peng et al. 2004). Tao et al. (2008) reported that the warming trends from 1981 to 2000 have had a negative impact on crop yield at 6 representative stations in northeast China. In monsoon affected countries such as India and Sri Lanka, rainfall is the key determinant of the productivity of rainfed crops. Challinor et al. (2003) showed that 50% of the variability in groundnut yield on the all-India scale could be explained by the variability in total seasonal rainfall from 1966 to 1995. Investigations on the effects of changes in mean annual temperature on agricultural crops (Wheeler et al. 2000, Challinor et al. 2007) have used crop–climate simulation models (Lobell et al. 2012, Asseng et al. 2013, Hawkins et al. 2013, Bassu et al. 2014, Li et al. 2015) and experiments (Lobell et al. 2011). The climatic conditions in semi-arid Africa vary from humid equatorial regimes, to the seasonally arid tropics, to subtropical Mediterranean climates, with hot and dry conditions and highly variable rainfall (IPCC 2014).

Since uncertainty in climate change projections remains substantial, it is vital to assess crop resilience of underutilised crops; Bambara groundnut can serve as a model in this. This study thus aims to understand how Bambara groundnut responds to core climate changes and specific climate projections for 3 diverse sites across Southern Africa through crop–climate modelling approaches.

2. METHODS

2.1. Geographic location

The suitability of 2 Bambara groundnut landraces, UN and S19-3, were evaluated for 3 Southern African locations: Gaborone, Botswana (24.35° S, 25.70° E; 1005 m elevation); Bloemfontein, South Africa (29.1° S, 26.3° E; 1353 m elevation); and Caprivi, Namibia (18.12° S, 23.635° E; 1020 m elevation) (Fig. 1). The Botswanian climate is similar to Caprivi, Namibia but slightly drier (527 mm mean annual rainfall). In South Africa, Bloemfontein has a cold semi-arid climate with sunny, dry days even during the winter growing season due to the high altitude; this contrasts with the hot semi-arid climate in both Gaborone and Caprivi.

2.2. Crop model

The AquaCrop interface and Plugin-ACsaV40 (v.4; www.fao.org/nr/water/aquacrop.html) were used to simulate multiple runs of the effect of climate change on the growth and yield performance of the 2 landraces across the 3 study sites in successive years.

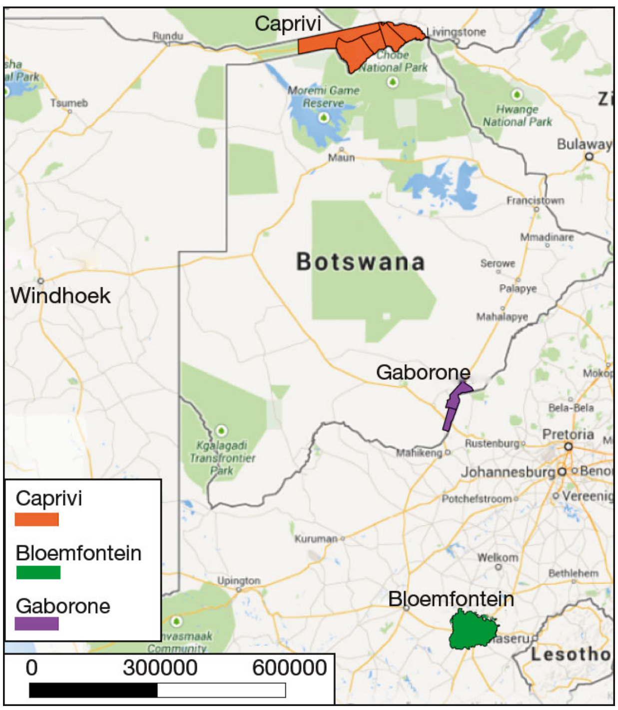

Fig. 1. Geographic location of the study area

The model was previously described by Raes et al. (2009), Steduto et al. (2009) and Vanuytrecht et al. (2014); therefore, only a summarised model description is presented here. AquaCrop consists of a soil–crop–atmosphere continuum with (1) soil-water balance, (2) crop growth, development and yield and (3) atmosphere-thermal regime, rainfall, evaporative demand and CO_2 concentration. The main features include (1) separation of evapotranspiration (*ET*) into crop transpiration (*Tr*) and soil evaporation (*E*), (2) a simple canopy growth and senescence model as the basis for the estimate of *Tr* and its separation from *E*, (3) final yield (*Y*) as the product of final biomass (*B*) and harvest index (*HI*), (4) segregation of water stress into 4 components: canopy growth, canopy senescence, *Tr* and *HI* and (5) temperature stress on yield.

The environment of the crop is specified in the climate component with 5 daily weather input variables: maximum and minimum temperatures, rainfall, reference evapotranspiration (*ETo*) and the mean annual CO_2 in the atmosphere. The *B* of the crop is simulated through cumulative transpiration and water productivity (*WP*) as

$$B = WP \times \sum Tr \qquad (1)$$

Each of the stress response factors, excluding *HI*, has its own stress coefficient *Ks*, which acts as an indicator of the stress intensity. In practise, *Ks* is a modifier or correction factor for its target model parameter. Its value varies from 0 to 1, with 0 representing maximum possible effect of the stress and 1 indicating no stress (Steduto et al. 2009). The calibrated crop files for temperature and drought stress at various growth stages of the 2 landraces S19 and UN, followed by independent validation at field sites in Swaziland and Botswana, were used for the present study (Karunaratne et al. 2011a).

2.3. Climate projections in Southern Africa

Agricultural Model Intercomparison and Improvement Project (AgMIP; Rosenzweig et al. 2013) protocols were used in the present climate projections. They were developed for projects over many regions, disciplines, temporal scales, and spatial scales in order to understand the effects of climate on food security. The AgMERRA climate data files (produced by the AgMIP Climate Team) were used for the present study; these contain climate time series at daily resolution covering 30 full planting and harvesting cycles for 1980–2009, providing the minimum number of years to represent climatology as defined by the World Meteorological Organization (WMO 1989, Ruane et al. 2014). In each data set, outlier values were identified and removed. In addition, inconsistent data entries were identified and removed (e.g. minimum temperature exceeding maximum temperature). Observations from neighbouring stations were compared in cases of unusual records.

The crop–climate projections of the current study include simulations for 30 growing seasons at baseline climate (1980–2009) and for mid-century (2040–2069), using a downscaled climate scenario from the Coupled Model Intercomparison Project (CMIP5). The most recent iteration of the CMIP5 (Taylor et al. 2012) utilized representative concentration pathways (RCPs) to cover the range of plausible greenhouse gas (GHG) concentrations past the year 2100, with RCP8.5 representing the most extreme scenario and RCP4.5 representing a lower concentrations scenario (Moss et al. 2010). The climate scenarios for the assessments were drawn from 20 general circulation models (GCMs) (Table 1) in the CMIP5 archive (Taylor et al. 2012), which were selected as those with available daily outputs extending to 2100 for both RCP8.5 and RCP4.5 in the online archive of the Program for Climate Model Diagnostics and Intercomparison (PCMDI).

2.4. Coordinated Climate–Crop Modeling Project (C3MP)

The Coordinated Climate–Crop Modeling Project (C3MP; Ruane et al. 2014) is an undertaking of the Agricultural Model Intercomparison and Improvement Project (AgMIP; Rosenzweig et al. 2013) that seeks to mobilize international crop modellers for a coordinated investigation of climate vulnerability and climate change impacts on agriculture. It is designed to analyse the sensitivities of crop responses to the core climate changes in carbon dioxide, temperature, and water (CTW), and to improve the utility of crop model applications. C3MP participants ran 99 sensitivity tests designed to efficiently sample the uncertainty space in projected temperature, water, and carbon dioxide changes (Table 2) projected by global climate models in CMIP5 (Taylor et al. 2012). Each sensitivity test consisted of 30 yr of simulation based on the 1980–2009 daily historical climate record, which was modified to add temperature changes, multiplied by precipitation change factors, and included imposed

Table 1. The growing season maximum (*T*max) and minimum temperatures (*T*min) and total growing season precipitation (RF) for the baseline period (1980–2009) and in mid-century (2040–2069) for 20 general circulation models (GCMs) under the RCP8.5 scenario in Botswana-Gaborone, South Africa-Bloemfontein and Namibia-Caprivi

Climate scenario	Botswana-Gaborone			South Africa-Bloemfontein			Namibia-Caprivi		
	Mean *T*max (°C)	Mean *T*min (°C)	Total seasonal RF (mm)	Mean *T*max (°C)	Mean *T*min (°C)	Total seasonal RF (mm)	Mean *T*max (°C)	Mean *T*min (°C)	Total seasonal RF (mm)
Baseline	29.3	15.2	235	26.0	9.9	310	31.1	17.3	339
ACCESS1-0 (A)	32.9	17.7	218	29.4	12.9	284	34.4	20.0	303
BCC-CSM1-1 (B)	33.1	17.6	188	29.3	12.4	267	34.0	19.6	307
BNU-ESM (C)	32.1	17.8	247	28.3	13.9	320	33.3	19.6	341
CanESM2 (D)	33.5	18.6	228	29.8	13.9	303	34.4	20.3	334
CCSM4 (E)	32.6	17.5	218	28.7	12.6	304	34.0	19.8	299
CESM1-BGC (F)	31.9	17.3	229	28.3	12.5	301	33.6	19.6	314
CSIRO-Mk3-6-0 (G)	33.3	18.3	226	30.3	13.2	185	34.6	20.2	298
GFDL-ESM2G (H)	31.5	17.1	274	28.3	12.1	312	32.8	19.0	366
GFDL-ESM2M (I)	32.0	17.3	213	28.5	12.0	278	33.0	19.1	343
HadGEM2-CC (J)	32.5	17.7	285	29.7	13.3	276	34.4	20.4	359
HadGEM2-ES (K)	32.1	17.6	265	28.3	13.0	329	33.6	20.5	373
INMCM4.0 (L)	31.9	17.1	191	28.7	11.9	263	32.8	18.6	307
IPSL-CM5A-LR (M)	33.2	18.4	193	29.0	13.7	331	34.3	20.3	312
IPSL-CM5A-MR (N)	32.8	18.8	226	28.9	13.8	339	33.9	20.3	356
MIROC5 (O)	31.8	17.4	252	28.2	12.4	309	33.6	19.5	340
MIROC-ESM (P)	31.7	17.0	175	29.5	13.0	266	34.9	19.8	257
MPI-ESM-LR (Q)	33.2	18.5	191	29.3	13.3	285	34.5	20.5	337
MPI-ESM-MR (R)	33.2	18.5	181	29.6	13.6	291	34.5	20.6	301
MRI-CGCM3 (S)	32.7	17.7	216	28.7	12.5	286	34.1	19.7	294
NorESM1-M (T)	31.6	16.8	259	27.9	12.0	294	33.3	18.9	340

Table 2. Climate metric ranges for C3MP climate sensitivity experiments. *T*: temperature; *P*: precipitation; $[CO_2]$: carbon dioxide concentration

Metric	Lower Bound	Upper Bound
ΔT	−1°C	+8°C
ΔP	−50%	+50%
$[CO_2]$	330 ppm	900 ppm

carbon dioxide concentration $[CO_2]$. Although the final years of the 21st century have $[CO_2]$ >900 ppm in RCP8.5 (the highest concentration pathway; Moss et al. 2010), C3MP is focused on 30 yr time slice climatologies, with the end-of-century period having a central year $[CO_2]$ of 801 ppm. Therefore, 900 ppm was selected as the upper bound for $[CO_2]$. The results presented here are some of the >1100 simulation sets contributed to C3MP (McDermid et al. 2014).

The results were statistically fit with an emulator to estimate 30 yr mean yield (*Y*) and the coefficient of variation (CV) for annual yields based on corresponding changes in temperature (*T*), rainfall (*P*) and $[CO_2]$ (*C*) according to the polynomial-based emulators shown in Eqs. (2 & 3).

$$Y(C, T, P) = a + b(T) + c(T)2 + d(P) + e(P)2 + f(C) + g(C)^2 + h(T \times P) + i(T \times C) + j(P \times C) + k(T \times P \times C) \quad (2)$$

$$\mathrm{CV}(C, T, P) = a + b(T) + c(T)2 + d(P) + e(P)2 + f(C) + g(C)^2 + h(T \times P) + i(T \times C) + j(P \times C) + k(T \times P \times C) \quad (3)$$

Note that the emulators were fit for *Y* and CV separately, such that the coefficients (*a*–*k*) are not equivalent for each equation. These emulators allow for the creation of impacts response surfaces, displaying Bambara groundnut model responses over the entire CTW change space.

2.5. Crop model efficiency criteria

To assess model performances and provide an objective evaluation of the 'closeness' of simulated vs. measured values, a number of indicators (RMSE, efficiency) were used. This evaluation involves an analysis of the simulated (S_i) and measured (M_i) values of yield from 'i = 1' to 'n' as last number used. Model efficiency (Eq. 4) and RMSE (Eq. 5) were used as criteria for model evaluation.

$$\text{Efficiency} = 1 - \sum_{i=1}^{n}(M_i - S_i)^2 \Big/ \sum_{i=1}^{n}(M_i - \overline{M})^2 \quad (4)$$

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n}(M_i - S_i)^2 \Big/ n} \quad (5)$$

3. RESULTS

3.1. AquaCrop simulations for base years

The previously calibrated AquaCrop model was tested for 3 independent experimental data sets from Botswana College of Agriculture, Gaborone, over 3 sowing dates (21 December, 15 January, 1 February) in the 2007/08 growing season. The probability of exceedance of observed yield by simulated yield for the 2 tested landraces UN and S19 are shown in Fig. 2. Simulation of in-season yield for S19 can be considered satisfactory, with relatively high model efficiency (0.72) and lower RMSE (0.23 t ha^{-1}). However, the UN landrace showed relatively lower model efficiency and higher RMSE (0.41 t ha^{-1}) compared to S19, indicating overestimation of the yield (Fig. 2). According to the observed yield records from the Botswana experiment, the 2 landraces performed differently with respect to yield. Generally, UN showed relatively higher yield than S19 and this was captured with the AquaCrop model.

3.2. Climate in the study regions

The growing season (1 January to 30 May) climate over the baseline period (1980–2009) and in mid-century (2040–2069) for the 20 GCMs (RCP8.5 scenario) in the 3 Southern African study sites is shown in Table 1. Botswana showed a rise (from baseline) in growing season temperatures of 2 to 4°C for mid-

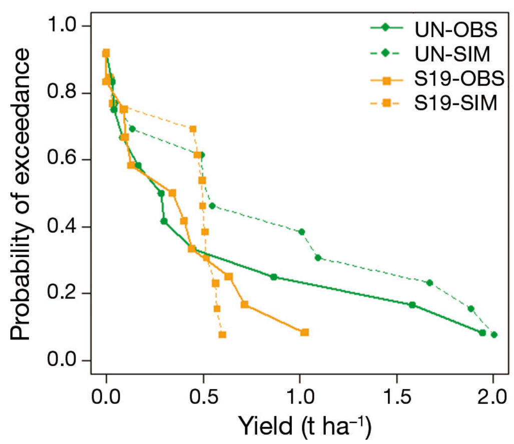

Fig. 2. Comparison of the exceedance probability of observed (—) and simulated (---) yield for 3 experimental data sets from Botswana College of Agriculture, Gaborone, Botswana over 3 sowing dates (21 December, 15 January, 1 February) separately aggregated for the landraces UN (green) and S19 (orange) in the 2007/08 growing season

century, with SDs in the range of ±4.0 to 6.0°C, whereas the seasonal total rainfall varied from −25 to +21% (decreased in 14 and increased in 6 out of the 20 GCMs tested). Overall, Botswana, which is the experimental site for AquaCrop evaluation and C3MP evaluation, revealed a 2 to 4°C rise in temperatures from baseline and −25 to +21% change in precipitation in mid-century for the 20 GCMs tested, at 557 ppm CO_2 (included in the C3MP climate sensitivity tests; Table 2). Similarly, South Africa showed a 2 to 4°C rise in growing season temperatures from baseline, with SDs of ±4.0 to 6.0°C. The seasonal total rainfall variability ranged from −17% (8 of 20 GCMs showed reductions of up to 17%) to +20% (12 of 20 GCMs showed increases of up to 20%). Similar to Botswana and South Africa, Namibia also showed increases in temperatures ranging from 2 to 4°C, with SDs of ±4.0 to 7.0°C across the GCMs tested. Rainfall showed a comparatively higher variability, ranging from −24% (11 of 20 GCMs) to +10% (9 of 20 GCMs).

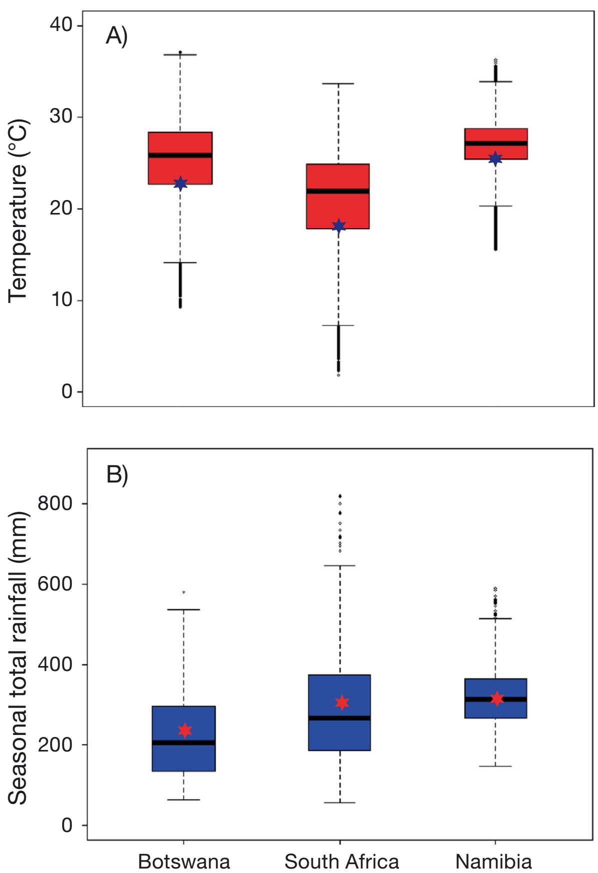

Fig. 3. Box and whisker plots for 30 yr (A) growing season mean temperature and (B) growing season total rainfall for 20 GCMs in mid-century under the RCP8.5 scenario. Horizontal lines: median; boxes: range between lower quartile and upper quartile; whiskers: minimum and maximum values in the data set excluding outliers; red asterisks: baseline

The detailed analysis of the climates for mid-century in the 3 study regions shows the diversity of changes in temperatures and rainfall across the 20 different GCMs.

The overall mid-century climates across the 20 GCMs tested are presented in Fig. 3. South Africa reported the lowest future mean temperature (22°C) over the growing season with climate change. Both Botswana and Namibia showed future growing season temperatures ranging from 26 to 28°C (Fig. 3A). Therefore, the baseline mean seasonal temperatures are below the −25% percentile of the box and whisker plots of GCM predicted temperatures across the 3 study sites. The predicted average seasonal total rainfall in the 3 study sites are 235, 310 and 339 mm for Botswana, South Africa and Namibia respectively, with decreasing trends, from baseline climates (Fig. 3B). Compared to the baseline (235 mm) that is between 50% and +25% percentile, Botswana showed a decrease in total seasonal rainfall in 15 and an increase in 5 out of the 20 GCMs tested. Similarly, South Africa showed a decrease in 16 and an increase in 4 out of the 20 GCMs, where baseline total seasonal rainfall (310 mm) is between 50% and +25% percentile of future predicted total seasonal rainfall. Namibia showed a decrease in 12 and an increase in 8 out of the 20 GCMs compared to the baseline (339 mm) that lies between −25% and 50% percentile of future predicted total seasonal rainfall.

3.3. C3MP results

The yield performances of the 2 landraces at Gaborone, Botswana were evaluated with climate sensitivity tests as explained in Section 2.4. The 3-dimensional CTW space was analysed using cross sections where one of the climate change metrics was kept at the baseline level (Fig. 4). The general response of Bambara groundnut yield in the Botswana experimental site is reported for both tested landraces. Both response surfaces indicate a strong increase in yield with elevated [CO_2]. Yields decline with lower precipitation and increase with wetter conditions. Yields increase with up to 3 to 4°C of warming, and then begin to decrease. The general decrease in yields under warmer and drier conditions with lower [CO_2], as well as the increase in yields in medium temperature increase, wetter and higher [CO_2] environments are consistent in both landraces. However, the individual responses of the 2 landraces tested differ in magnitude. UN is more sensitive to CO_2 and temperature increases than S19. These emulators clearly

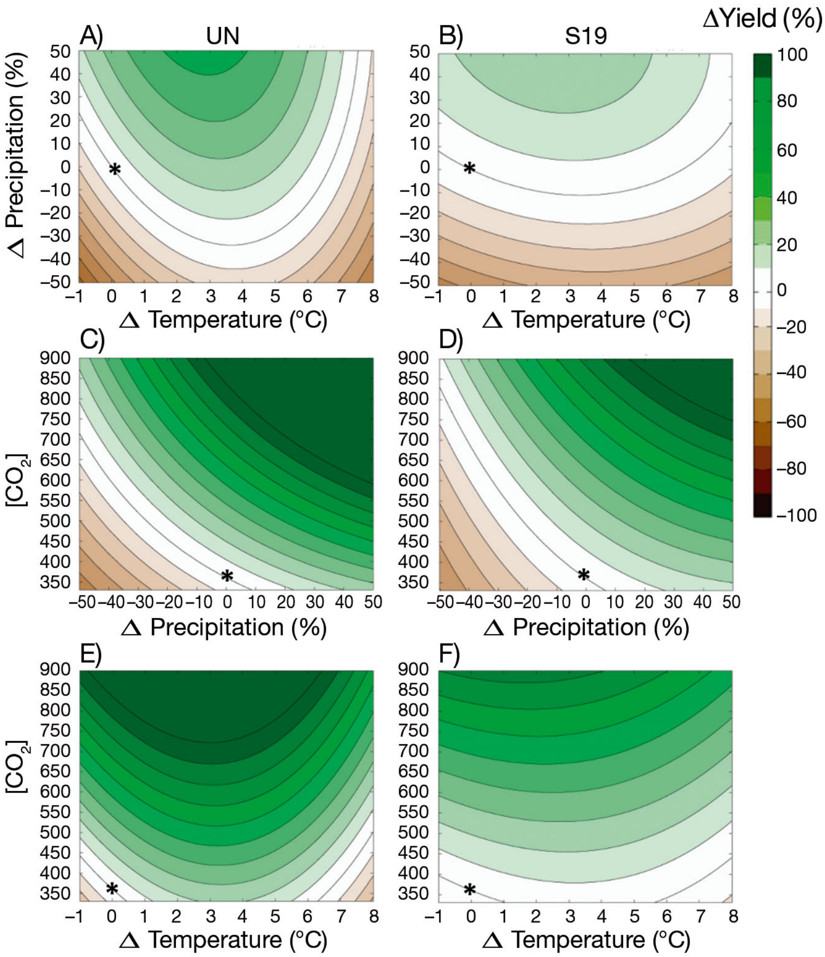

Fig. 4. Cross sections of crop model emulators based on sensitivity test results for percent changes (relative to baseline conditions [✱], i.e. no change in temperature or precipitation and 360 ppm [CO_2]) in mean Bambara groundnut yield (A,C,E: UN landrace; B,D,F: S19 landrace) in Gaborone, Botswana, for (A,B) temperature and precipitation response at baseline [CO_2]; (C,D) precipitation and [CO_2] at baseline temperature; and (E,F) temperature and [CO_2] at baseline precipitation

explain the crop model responses by identifying nonlinearities in crop response, exploring interactions in CTW response, and quickly assessing climate change scenarios.

3.4. AquaCrop yield prediction for the future scenario

The AquaCrop yield predictions for the baseline period revealed diverse yield performances across the 3 study sites for the 2 landraces tested (Fig. 5). In Botswana the 30 yr mean yield of S19 (1.4 ± 0.9 t ha^{-1}) is ~27% higher than that of UN (1.0 ± 1.1 t ha^{-1}) which showed higher yield deviations. South Africa followed the opposite trend for the 2 landraces over the baseline period, with 15% higher mean yield in UN (0.93 ± 1.3 t ha^{-1}) than in S19 (0.8 ± 1.0 t ha^{-1}). In Namibia, the baseline mean yield was similar to that of Botswana, with ~34% higher mean yield for S19 (1.7 ± 1.2 t ha^{-1}) than for UN (1.1 ± 0.94 t ha^{-1}), indicating the highest yield gap between the 2 landraces under actual climates. S19 reported a generally higher mean yield compared to UN under actual climate over the 1980–2010 period in warmer and drier regions (i.e. Botswana and Namibia). The higher baseline yield of UN compared to S19 in South Africa is associated with the relatively cooler growing conditions that favour the Swaziland landrace (Table 1).

The predicted yields for mid-century (2040–2069) under the high emission scenario (RCP8.5) were statistically analysed for evaluation of significant difference; the percentages of mean yield changes compared to baseline mean yields are presented in Fig. 6. The detailed analysis of individual GCM yield predictions showed that there are 50 and 70% probabilities of increasing the yield for UN and S19 respectively, with significant ($p < 0.05$) positive trends both in GFDL-ESM2G (H; 84% for UN) and NorESM1-M ESM2G (T; 78% for S19). The clear climate signal for the highest yield gain in GFDL-ESM2G (H) and NorESM1-M (T) is a 3°C rise in growing temperatures, which is favourable for growing Bambara groundnut in Botswana (Table 1). On average, UN and S19 respectively revealed 30 and 55% mean yield increases for mid-century compared to mean yield with actual observed climates in Botswana, across the 20 GCMs tested (Fig. 6).

The detailed analysis of AquaCrop yield predictions for South Africa-Bloemfontein for mid-century showed 80 to 90% probability of significant yield gain compared to baseline years ($p < 0.05$) in both landraces. The highest yield increase for UN was 135% ($p < 0.05$), while for S19, this was up to 200%, thus showing the favourable conditions of elevated CO_2 and 2 to 4°C rise in temperatures in South Africa for Bambara groundnut. The Namibian landrace S19 has not achieved its potential yield due to cooler growing conditions in the baseline climate. On average, UN and S19 showed mean yield gains of 61 and

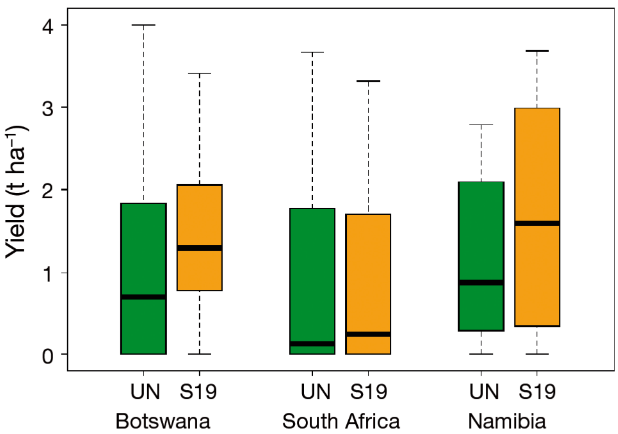

Fig. 5. Box and whisker plots of mean yield over the baseline period (1980–2010) at Botswana-Gaborone, South Africa-Bloemfontein and Namibia-Caprivi for the 2 landraces UN (green) and S19 (orange). Horizontal lines: median; boxes: range between lower and upper quartiles; whiskers: minimum and maximum values in the data set excluding outliers

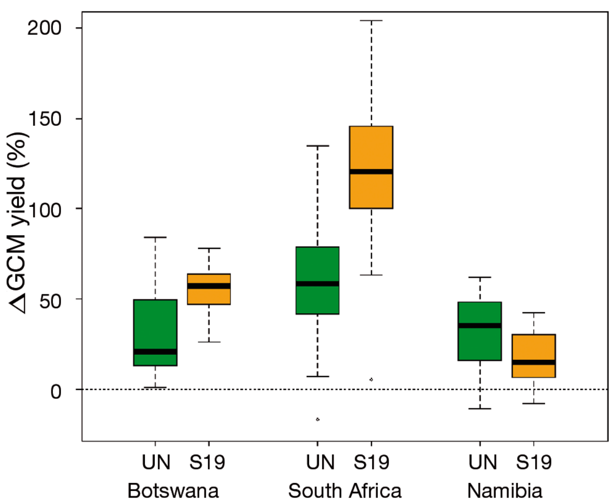

Fig. 6. Box and whisker plots of mean yield changes (%) in 20 GCMs (A–T in Table 1) under the RCP8.5 scenario in mid-century (2040–2069) at Botswana-Gaborone, South Africa-Bloemfontein and Namibia-Caprivi for the 2 landraces UN (green) and S19 (orange). Horizontal lines: median; boxes: range between lower and upper quartiles; whiskers: minimum and maximum values in the data set excluding outliers

122%, respectively, compared to mean yield under baseline climate in South Africa, across the 20 GCMs tested. The yield predictions for the 20 GCMs for both landraces revealed positive yield performances in South Africa under climate change predictions (Fig. 6).

The overall yield predictions for Namibia for mid-century under the 20 climate change scenarios of CMIP5 followed a similar trend as that in Botswana. The exceedance probability of predicted yield showed ~50% probability of increasing the yield in both landraces, with significant positive trends ($p < 0.05$) for GFDL-ESM2G (H; 62% in UN) and INMCM4.0 (L; 42% in S19); this indicates that a ~1°C rise in temperatures associated with wet conditions is favourable (Table 1). Yield reduction of up to −11% has ~50% probability. However, Namibia has been experiencing relatively warmer and drier conditions compared to Botswana and South Africa over the last 3 decades; under a changed climate, conditions would not be favourable for the growth of Bambara groundnut as a major crop in Namibia. Overall, UN and S19 revealed 30 and 17% mean yield increases (lower than values for Botswana) for mid-century compared to mean yield with actual observed climates in Namibia, across the 20 GCMs tested (Fig. 6).

4. DISCUSSION

The 3 sites tested in the present study — Botswana-Gaborone, South Africa-Bloemfontein, Namibia-Caprivi — revealed differences in yield performances for the 2 landraces of Bambara groundnut (UN, S19) both under current observed climate over the baseline period (1980–2009) and in mid-century (2040–2069) under climate change scenarios of RCP8.5. In Botswana, there is a 50 to 70% probability of increasing yields based on the 20 GCMs in the CMIP5 archive. Similarly, Namibia showed a 50% probability of positive yield trends for both landraces. The average yield across GCMs revealed 30 and 55% mean yield increases from baseline mean yield for UN and S19 respectively in Botswana, and 30 and 17% mean yield increases for UN and S19 respectively in Namibia. Similar yield trends for the 2 landraces were observed in South Africa, but with 80 to 90% probability of increasing the yield from baseline mean yield (mean values of 61 and 122% for UN and S19 respectively). The highest yield potential observed in South Africa under climate change shows that Bambara groundnut has not reached its potential yield with actual climates, and would be favoured by increasing temperatures and rainfall. Both Botswana and Namibia are already experiencing higher 30 yr mean temperatures along with dry conditions compared to South Africa, and further warming and rainfall decline in some of the GCMs would impose limitations on yield. There is a clear indication that the Namibian landrace S19 has more potential in Botswana than the Swaziland landrace UN. This difference between the 2 landraces is linked with the C3MP results in Botswana and indicates that UN may be more sensitive to temperature and CO_2 than S19. The ~200% yield gain in S19 in South Africa clearly shows the higher yield advantages associated with further warming trends and wetter conditions.

The observed results are supported by previous detailed studies imposing temperature (23 ± 5°C, 33 ± 5°C) and drought stress on the 2 landraces UN and S19; these studies were conducted at the Tropical Crop Research Unit (Sutton Bonington Campus, University of Nottingham) over the summer months of 2006, 2007 and 2008 (Karunaratne 2009). It was evident that Bambara groundnut landraces, especially S19, survived with high yield potentials under high temperature (33 ± 5°C) and drought stress. This strong experimental evidence was used in calibrating the AquaCrop model in response to stress coefficients (Karunaratne et al. 2011a).

The yield simulation results of the present study agree with those of Tingem & Rivington (2009) who reported that projected changes in climate are advantageous for some genotypes, resulting in beneficial feedback from increased CO_2 and elevated temperature. Simulation results for C3 crops showed substantial gains under climate change without any adaptation (2020s, 2080s); using a new cultivar, yields of Bambara groundnut were almost tripled due to increased length of the growing period and the positive effects of higher [CO2] (Tingem & Rivington 2009). These results highlight the need to search for and promote new crop options as well as practices and methods that maximise utilization of prevalent crop and climatic combinations.

A detailed review evaluating climate change impacts on 3 major global cereals (wheat, maize, rice) showed that maximum lethal temperatures are similar for the 3 crops and range from 43° to 48°C (Sanchez et al. 2014). The highest SE of a lethal temperature (2.9°C) is found in maize; this may be because, of the 3 crops, maize is planted over the widest range of latitude, ranging from ca. 60° N in Finland and northern Eurasia to 40° S in Australia, Africa and South America. Standard lethal temperature errors for wheat and rice are smaller and close to each other. Minimum lethal temperatures differ in a broad range, showing that wheat has the lowest average minimum (−17.2°C); maize dies at temperatures just below freezing and rice at temperatures under 5°C. According to Sanchez et al. (2014) all threshold temperatures are important for crop development and growth but we wish to highlight two of them that are especially important for yields. (1) The reduction in grain set caused by overstepping these thresholds can be dramatic (Wheeler et al. 1996), and (2) all 3 crops can suffer large yield losses due to sterility at high extreme temperatures. An under-researched topic is the mechanisms by which high temperatures affect pollen meiosis in cereals and plants in general.

Bambara groundnut landraces originate from various locations across semi-arid Africa. Thus, they exhibit diverse adaptations to different agro-ecological environments. The variation in predicted yield performances of the 2 landraces is well correlated with previous studies. Experimental evidence from previous studies at Nottingham (Mwale et al. 2007, Karunaratne et al. 2010) showed that the Namibian landrace S19 had a faster rate of development (which led to earlier maturity), and also more economical water use compared to other landraces. In contrast, UN had slower development in most of the physiological traits studied. A detailed evaluation of UN and S19 responses to drought (Mwale et al. 2007) reported that the short phenology and fast development of S19 may reflect its adaptation to low rainfall (365 mm mean annual rainfall) and warm conditions, with shorter growing periods. In contrast, UN showed its agro-ecological adaptation to relatively cooler, high rainfall (1390 mm mean annual rainfall) conditions, with longer growing periods. Currently, there is no detailed information about the temperature threashold: base (T_{base}), optimum (T_{opt}) and ceiling (T_{high}) for UN and S19. The previous models (BAMGRO; Karunaratne et al. 2011b) use 8.5°, 28° and 38°C for UN and 12°, 30° and 45°C for S19-3 as base, optimum and ceiling temperatures, respectively, based on glasshouse experimental data. The growth and developmental performance of the landraces used appear to be closely related to rainfall amounts, daily mean temperatures and growing-season lengths in the countries that we studied, showing their agro-ecological adaptation. Based on the climates of Namibia, South Africa and Botswana, it is clear that Bambara groundnut has broad climatic adaptation, and this adaptability is reflected in the model simulations.

5. CONCLUSIONS

This study evaluated crop–climate modelling using a specific underutilised crop and recognised crop models (AquaCrop) to link available climate databases within a geospatial information system framework (AgMIP). This is a preliminary case study evaluating the productivity of Bambara groundnut genotypes under baseline and future climate scenarios in Southern Africa. C3MP results for Botswana reported a considerable diversity in yield performances. Yields are improved in Southern Africa under a changed climate, with positive yield trends for the Namibian original landrace S19, this potential being greater in South Africa. The Swaziland landrace UN is more sensitive to temperature and [CO_2] than the Namibian landrace S19. Thus, the Namibian landrace S19 showed higher climate resilience with respect to yield. Bambara groundnut therefore holds tremendous potential for increased yields at temperatures of up to ~31°C, with temperatures >31°C being likely to decrease yields. Moreover, many regions in Southern Africa (e.g. Botswana, South Africa and Namibia) can utilize Bambara groundnut successfully for the coming decades. Furthermore, the current study demonstrated that genetically distinct material from matched climatic conditions can be used to predict optimal selections of parental germplasm for breeding material suited to different locations for a climate-resilient future.

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