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Is cassava the answer to African climate change adaptation?

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Abstract

This paper examines the impacts of climate change on cassava production in Africa, and questions whether cassava can play an important role in climate change adaptation. First, we examine the impacts that climate change will likely have on cassava itself, and on other important staple food crops for Africa including maize, millets, sorghum, banana, and beans based on projections to 2030. Results indicate that cassava is actually positively impacted in many areas of Africa, with –3.7% to +17.5% changes in climate suitability across the continent. Conversely, for other major food staples, we found that they are all projected to experience negative impacts, with the greatest impacts for beans (-16% ± 8.8), potato (-14.7 ± 8.2), banana (-2.5% ± 4.9), and sorghum (-2.66% ± 6.45). We then examined the likely challenges that cassava will face from pests and diseases through the use of ecological niche modeling for cassava mosaic disease, whitefly, brown streak disease and cassava mealybug. The findings show that the geographic distribution of these pests and diseases are projected to change, with both new areas opening up and areas where the pests and diseases are likely to leave or reduce in pressure. We finish the paper by looking at the abiotic traits of priority for crop adaptation for a 2030 world, showing that greater drought tolerance could bring some benefits in all areas of Africa, and that cold tolerance in Southern Africa will continue to be a constraint for cassava despite a warmer 2030 world, hence breeding needs to keep a focus on this trait. Importantly, heat tolerance was not found to be a major priority for crop improvement in cassava in the whole of Africa, but only in localized pockets of West Africa and the Sahel. The paper concludes that cassava is potentially highly resilient to future climatic changes and could provide Africa with options for adaptation whilst other major food staples face challenges.

Keywords: cassava, climate change, EcoCrop, Africa, breeding, pests and diseases

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1. Introduction

Kamukondiwa (1996) discussed the merits of cassava for adapting African agriculture to climate change, and fifteen years later the challenges of climate change and the needs for identifying solutions are even greater. Studies have predicted significant impacts from climate change on African agriculture (Thornton et al., 2011), although estimates of impacts vary widely between authors (Challinor and Wheeler, 2008a).

Cassava (*Manihot esculenta*) is the crop with the highest total production in Africa, with 118 million MT of productions across the continent in 2010, contributing significant energy input to the population with an average 196 kcal/capita/day in 2008 (FAO, 2010). It is a major staple for more than 500 million people in Africa, and is renowned for its drought tolerance and hardiness in stressful environments (El-Sharkawy, 2004). Of the few studies which have quantified the impacts or responses of cassava to climate change, and all have found cassava to be the least affected crop when compared with other major staples such as maize, sorghum and millets. Liu et al. (Liu et al., 2008) used the GIS-based Environmental Policy Integrated Climate (GEPIC) model to evaluate impacts on cassava production across Sub-Saharan Africa finding a change in production to 2030 of -2% to +1% depending on the SRES Scenario. This matches with Lobell et al. (Lobell et al., 2008) who found cassava to moderately benefit from climate change by 2030 with an average increase of 1.1% in production from 2000 through the use of statistical models. Schenkler and Lobell (Schlenker and Lobell, 2010) found a decrease in production of 8% for cassava by mid-century, compared with much more severe impacts for maize (-22%), sorghum (-17%) and millets (-17%). All studies report uncertainties in these estimates due to the underlining climate projections, or the model that captures crop-climate response. Furthermore, these studies do not take into account CO_2 fertilization where there is no consensus on the response of cassava to increased CO_2 concentrations. Gleadow et al. (2009) reported reduced growth in cassava under enhanced CO_2 concentrations as well as increased cyanide concentrations in leaves, but Ort et al. (this issue) shows contrasting results based on Free Air CO_2 Enrichment (FACE) experiments conducted in field trials in Illinois where root biomass was found to increase under elevated CO_2.

Insect pests and plant diseases of cassava are known to substantially affect storage root weight, increasing the yield gap in developing countries, where it is mostly grown (Olsen and Schaal, 1999). Cassava brown streak and mosaic viruses, incidence of whiteflies, mealybugs, and the widely-spread cassava green mite significantly reduce cassava yields and pose a constraint to poor farmers with little or no response capacity (Herrera Campo et al., 2011; Yaninek and Herren, 1988). Very little information is available on the distribution of cassava pests and diseases (Herrera Campo et al., 2011; Trujillo et al., 2004; Yaninek and Herren, 1988), particularly within the context of climate change, although it is stated that climate change could result in increased incidence, further increasing economic losses and vulnerability (Ceballos et al., 2011).

This paper aims to provide an update to Kamukondiwa (1996), taking a quantitative rather than qualitative approach, and building on other studies that have modeled climate change impacts on cassava. This paper examines if cassava really is a crop of merit for adaptation to climate change in a 2030 world. Specifically, the objectives are to:

1. Identify the climatic changes projected for cassava growing regions in Africa for 2030 and beyond
2. Quantify the impacts of these changes on cassava climate suitability in Africa
3. Quantify the impacts of these changes on other major staples in Africa
4. Quantify the impacts of climate change on major cassava pests and diseases in Africa
5. Identify some of the challenges that climate change might bring for crop improvement over the coming decades

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We then bring the above analyses together to provide an outlook for cassava under the context of climate change.

2. Materials and Methods

This paper combines data and models to evaluate the impacts of climate change on cassava and other staples in Africa, and evaluate *ex ante* the potential benefits of crop improvement options for supporting adaptation in the cassava crop. The approaches comprise of 1) definition of current and future climate projections for the analysis and analysis of climate changes in cassava growing regions, 2) prediction of current climate constraints and future impacts of climate change on cassava climate suitability, 3) prediction of impacts on other major staple crops in Africa and comparison with predicted impacts on cassava to explore contrasting and/or similar responses, 4) evaluation of impacts on major pests and diseases, and 5) *ex ante* evaluation of crop improvement scenarios.

2.1. Study area

This study focuses on the African continent only, comprising North Africa and Sub-Saharan Africa, although >99% of production occurs in East, West, Central and Southern Africa (FAO, 2010). We classified countries in the region according to well-defined and documented areas (Lobell et al., 2008) (Figure S1).

2.2. Input climate data

2.2.1. Current climate data

High quality distributed data on current climate has always been a constraint for agricultural impact assessment, especially in Africa where meteorological stations are scarce. Quality of weather and climate data (if available) is poor. The approach used in this research allows us to use large-scale monthly datasets (Sect 2.3), for which accuracy and availability is known to be much better, as compared to daily data (Hijmans et al., 2005; Peterson and Vose, 1997; Richardson, 1981). Here we used the WorldClim dataset (Hijmans et al., 2005), publicly and freely available at http://www.worldclim.org. WorldClim was developed using ~47,000 weather stations with monthly information on precipitation, ~23,000 stations with mean temperature data and ~13,000 locations with diurnal temperature range data, passed through a quality checking algorithm and then used to develop a continuous climate surface using a thin plate spline algorithm (Hutchinson, 1995; Hutchinson and de Hoog, 1985), with elevation, latitude and longitude as independent variables (Hijmans et al., 2005). The data represent long term (1950-2000) monthly means of maximum, minimum, mean temperatures and total rainfall, at 30 arc-seconds (~1 km at the equator) for every land area of the globe.

WorldClim data was downloaded at the resolution of 30 arc-seconds, restricted to Africa (Sect. 2.1) and aggregated to the resolution of 10 arc-minutes (~20 km at the equator) in order to reduce computational time and storage needs. The aggregation of these data is not expected to bias the results because (1) the major topographic gradients are still present at 10 arc-minutes, and (2) a regional and national-level modeling technique was used, which is unlikely to be affected. With the aggregated data two datasets were produced:

(a) WCL-MM: comprising the original monthly means of maximum, minimum and mean temperature and the total monthly rainfall, and
(b) WCL-BC: comprising a set of 19 bioclimatic indices, derived from WCL-MM following the procedure of Ramirez and Bueno-Cabrera (2009). These indices reflect mean and extreme annual averages and are thus associated with crop, pest and disease species development (Table 1) (Herrera Campo et al., 2011; Schroth et al., 2009).

WCL-MM were used for analyzing the changes in cassava growing regions (Sect. 2.3) and for crop modeling (Sect. 2.4, 2.5, and 2.7), whereas WCL-BC were used in the modeling of pests and diseases (Sect. 2.6) (Herrera Campo et al., 2011).

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Table 1 List of derived bioclimatic variables used in the analysis

ID	Variable name	Units
P1	Annual mean temperature	ºC
P2	Mean diurnal temperature range	ºC
P3	Isothermality	N/A
P4	Temperature seasonality (standard deviation)	ºC
P5	Maximum temperature of warmest month	ºC
P6	Minimum temperature of coldest month	ºC
P7	Temperature annual range	ºC
P8	Mean temperature of wettest quarter	ºC
P9	Mean temperature of driest quarter	ºC
P10	Mean temperature of warmest quarter	ºC
P11	Mean temperature of coldest quarter	ºC
P12	Annual precipitation	mm
P13	Precipitation of wettest month	mm
P14	Precipitation of driest month	mm
P15	Precipitation seasonality (coefficient of variation)	%
P16	Precipitation of wettest quarter	mm
P17	Precipitation of driest quarter	mm
P18	Precipitation of warmest quarter	mm
P19	Precipitation of coldest quarter	mm

2.2.2. Future climate data

We downloaded 20th century realizations (20C3M, hereafter) and projections of the SRES-A1B emissions scenario (IPCC, 2000) of 24 different Global Climate Models (GCMs, Table 2) from the IPCC Earth System Grid (ESG) model output repository (PCMDI, 2007). Downloaded data consisted in monthly time series of predicted 20th century climate (from 1900 through 2000, generally) and monthly time series of projected future conditions (2001-2100, generally) for the SRES-A1B emissions scenario in NetCDF format, for the same variables available in WorldClim (Sect. 2.2.1). These data were restricted to Africa (Sect. 2.1). The 20C3M predictions were assembled together and monthly climatology of the period 1961-1990 was calculated for the four variables for each month. The SRES-A1B projections were used in a similar way to generate monthly climatology for the 2030s period (2020-2049), centered in 2035, as suggested by the IPCC (IPCC, 2007; PCMDI, 2007). The downscaling method of Ramirez and Jarvis (2010) was used to increase the resolution of GCM outputs to match that of WorldClim. Briefly, the procedure consists in computing the anomalies of temperature and precipitation for each GCM (difference between future and current), interpolating them using a two-dimensional spline algorithm, and then adding these interpolated anomalies to the current distribution of climates in WorldClim. This method relies on the assumptions that (1) patterns of change do not have large spatial variations and (2) relationships between variables hold in time, quality of results is not expected to be affected (Mulligan et al., 2011; Ramirez-Villegas et al., 2011). Multiple GCMs were used in order to properly quantify uncertainty, at the expense of mechanistic detail in downscaling using one single (or a limited number of) regional climate model (RCM) (Baigorria et al., 2007; Challinor and Wheeler, 2008a).

Using the monthly means of the individual GCMs, three calculations were performed for being used in the modeling:

(a) GCM-MM: GCM-specific (Table 2) monthly means of maximum, minimum and mean temperature and monthly total rainfall were used individually as a direct input to the crop modeling of Sect. 2.4 and 2.5.
(b) ENS-MM: GCM-specific monthly data were averaged per variable to generate a GCM ensemble of monthly data to be used in the abiotic breeding priorities modeling (Sect. 2.7)
(c) ENS-BC: ENS-MM data were used to generate the 19 bioclimatic indices (Table 1) as done for WCL-BC. These data were used in the pests and diseases modeling (Sect. 2.6).

2.3. Projected climatic changes for cassava growing regions

The GCM-MM and WCL-MM data was used to calculate predicted GCM-specific changes in total annual precipitation (mm) and annual mean temperature (°C) for each country of our study area in the areas where the crop is reported to be grown in 2000 based on SPAM (Spatial Allocation Model) crop distribution data (FAO, 2010; You et al., 2009).

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Table 2 Global Circulation Models used in the analyses

Model	Country	Atmosphere*	Ocean*
BCCR-BCM2.0	Norway	T63, L31	1.5x0.5, L35
CCCMA-CGCM3.1 (T47)	Canada	T47 (3.75x3.75), L31	1.85x1.85, L29
CCCMA-CGCM3.1 (T63)	Canada	T63 (2.8x2.8), L31	1.4x0.94, L29
CNRM-CM3	France	T63 (2.8x2.8), L45	1.875x(0.5-2), L31
CSIRO-Mk3.0	Australia	T63, L18	1.875x0.84, L31
CSIRO-Mk3.5	Australia	T63, L18	1.875x0.84, L31
GFDL-CM2.0	USA	2.5x2.0, L24	1.0x(1/3-1), L50
GFDL-CM2.1	USA	2.5x2.0, L24	1.0x(1/3-1), L50
GISS-AOM	USA	4x3, L12	4x3, L16
GISS-MODEL-EH	USA	5x4, L20	5x4, L13
GISS-MODEL-ER	USA	5x4, L20	5x4, L13
IAP-FGOALS1.0-G	China	2.8x2.8, L26	1x1, L16
INGV-ECHAM4	Italy	T42, L19	2x(0.5-2), L31
INM-CM3.0	Russia	5x4, L21	2.5x2, L33
IPSL-CM4	France	2.5x3.75, L19	2x(1-2), L30
MIROC3.2-HIRES	Japan	T106, L56	0.28x0.19, L47
MIROC3.2-MEDRES	Japan	T42, L20	1.4x(0.5-1.4), L43
MIUB-ECHO-G	Germany/Korea	T30, L19	T42, L20
MPI-ECHAM5	Germany	T63, L32	1x1, L41
MRI-CGCM2.3.2A	Japan	T42, L30	2.5x(0.5-2.0)
NCAR-CCSM3.0	USA	T85L26, 1.4x1.4	1x(0.27-1), L40
NCAR-PCM1	USA	T42 (2.8x2.8), L18	1x(0.27-1), L40
UKMO-HADCM3	UK	3.75x2.5, L19	1.25x1.25, L20
UKMO-HADGEM1	UK	1.875x1.25, L38	1.25x1.25, L20

*Horizontal (T) resolution indicates number of cells in which the globe was divided for each component of the coupled climate model (i.e. atmosphere, ocean). Vertical (L) resolution indicates the number of layers in which the atmosphere was divided. When a model is developed with different latitudinal and longitudinal resolutions, the respective cellsizes (LonxLat) in degrees are provided instead of a unique value

Any climate change projection must be analyzed as being in a range of plausible responses to a given assumed or modeled future condition (Moss et al., 2010). Impact assessment methods are sensitive to uncertainties in the underlying climate data, and hence these must be considered when assessing crop responses to combinations of increasing temperatures, varied precipitation patterns and increased CO_2 concentrations (Challinor et al., 2007; Fuhrer, 2003). Uncertainties in climate change impact assessment arise from the projected greenhouse gas concentrations (Moss et al., 2010), the response of the climate system to these conditions, the climate models used to predict such behavior (e.g. model formulation, parameterized physics) and the uncertainties related to the impact assessment model itself and its usage over future climate conditions (Challinor et al., 2009; Challinor and Wheeler, 2008a). Assessing the climate-inherent uncertainty in climate change impact assessment projects explicitly entails the usage of different GCMs. In order to account for this, the individual GCM predicted changes were averaged and plotted in a scattergram with respective standard deviations indicative of uncertainties.

2.4. Impacts on cassava climate suitability

To assess the impacts of climate change the EcoCrop model was used. Originally developed by Hijmans et al. (2001) and fully described by Ramirez-Villegas et al. (2011), EcoCrop is a simple mechanistic model designed to operate at a monthly time scale and capable of analyzing the geography of crop suitability with regards to climate conditions. The model uses

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environmental ranges to determine the main niche of a particular crop and numerically assesses the environmental conditions to determine a potential climatic suitability rating (Hijmans et al., 2001; Ramirez-Villegas et al., 2011). This suitability rating is related with agricultural yields, although the relationship is difficult to capture (Ramirez-Villegas et al., 2011), partly because it is fairly dependent on the strength of the climate signal in agricultural yields (which is not always high). To achieve a particular prediction, a parameter set defining the optimal and marginal temperatures and rainfall at which the crop can grow is defined, ideally via statistical data analysis (Ramirez-Villegas et al., 2011), but also through literature and expert consultation (Beebe et al., 2011; FAO, 2000).

Ramirez-Villegas et al. (2011) used the EcoCrop model to predict the impacts of climate change on sorghum and found that the model agrees with other approaches such as statistical regressions. Other authors have parameterized and used the model in the context of climate change impact assessment for a number of crops (Beebe et al., 2011; Ceballos et al., 2011; Ramirez et al., 2011; Schafleitner et al., 2011), and have developed parameterizations for assessing regional climate constraints and adaptation options (i.e. breeding) (Beebe et al., 2011). Despite EcoCrop being a simple agroecological zonification model, it is useful for regional, continental and global scale analyses for food security assessments in which the required level of detail is not too high (Ramirez-Villegas et al., 2011). We decided to use EcoCrop for the following reasons:

- We predicted impacts of climate change over Africa with the maximum level of detail at the national or sub-national level, hence a more detailed approach seems unnecessary,
- More complex mechanistic approaches for cassava are rather scarce or highly inaccurate, mainly due to the difficulty in modeling an intermediate C3/C4 physiology (El-Sharkawy, 2005, 1985),
- EcoCrop has already been calibrated and expert-assessed for cassava by Ceballos et al. (2011),
- The usage of EcoCrop allows us to analyze a broader number of crops, and hence different responses to stresses,

As in any model, caveats exist and are summarized by previous studies (Beebe et al., 2011; Ramirez-Villegas et al., 2011; Ramirez et al., 2011), indicating that the model should be used with caution. These caveats include the inability of the model to capture the effect of short-duration stress periods, the lack of a clear relationship between the suitability index and crop yields, the scale at which the model can suitably be applied, the lack of representation of soil-related processes and constraints, among others.

In this research, the EcoCrop model was used as parameterized by Ceballos et al. (Ceballos et al., 2011) (Table 3). We first performed a suitability prediction for present conditions (i.e. WCL-MM, Sect. 2.1.1) and then projected the model onto each of the 24 different GCMs (GCM-MM, Sect. 2.1.2). For each projection, the change in suitability was calculated on a pixel basis and the ensemble mean, 25th and 75th percentiles were calculated as measures of suitability impact. The fraction of GCMs agreeing in direction of change and the standard deviation among GCMs were also calculated as measures of uncertainty (Ramirez-Villegas et al., 2011). These results were mapped using R version 2.13.2 (R Development Core Team, 2011). Five impact metrics were derived on a regional and national level for each GCM-MM individual prediction:

(a) the overall suitability change (average % change of all pixels);
(b) the average suitability change in positively impacted areas (i.e. areas increasing suitability);
(c) the area positively impacted (km^2);
(d) the average suitability change in negatively impacted areas (i.e. areas decreasing suitability);
(e) the area negatively impacted (km^2);

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Table 3 Parameter sets used for the crop suitability modeling, as reported in original studies or in the FAO-EcoCrop database

Crop	Species	GS[2]	T_{KILL} (°C)	T_{MIN} (°C)	T_{OPMIN} (°C)	T_{OPMAX} (°C)	T_{MAX} (°C)	R_{MIN} (mm)	R_{OPMIN} (mm)	R_{OPMAX} (mm)	R_{MAX} (mm)	Data Source[3]
Cassava	*Manihot esculenta* C.	8	0.0	15.0	22.0	32.0	45.0	300	800	2200	2800	CE2011
Sorghum (N) [1]	*Sorghum bicolor* M.	6	0.5	4.1	13.6	24.6	26.0	160	500	1800	2780	RV2011
Sorghum (X) [1]	*Sorghum bicolor* M.	6	14.5	17.8	26.7	37.4	39.1	160	500	1800	2780	RV2011
Maize	*Zea mays* L. subsp. *mays*	7	0.0	10.0	18.0	33.0	47.0	400	600	1200	1800	F2000
Banana	*Musa acuminata* C.	12	10.0	16.0	24.0	27.0	35.0	700	1000	1300	5000	R2011
Potato	*Solanum tuberosum* L.	4	-0.8	3.7	12.4	17.8	24.0	150	250	325	785	S2011
Millet	*Panicum miliaceum* L.	6	0.0	15.0	20.0	32.0	45.0	200	500	750	1000	F2000
Beans	*Phaseolus vulgaris* L.	3	0.0	13.6	17.5	23.1	25.6	200	363	450	710	B2011

[1] The original study or Ramirez-Villegas et al. (2011) reported two parameter sets given by two adaptive ranges of the crop. These were merged into one single suitability prediction using the methods reported in the same study
[2] Growing season duration in months
[3] Studies used for parameterizing EcoCrop. CE: Ceballos et al. (2011); RV: Ramirez-Villegas et al. (2011); F2000: FAO (2000); R2011: Ramirez et al. (2011); S2011: Schafleitner et al. (2011); B2011: Beebe et al. (2011).

The results are displayed in tables. Results from this modeling exercise are also compared with previous studies on cassava climate impacts from Lobell et al. (2008) and Schlenker and Lobell (2010).

2.5. Impacts on other staple crops

In looking at cassava as an adaptation option for Africa, it is important not to assess the crop in isolation, but rather examine the impacts of climate change on cassava and compare with other important African staples. To do this, five other important food crops for Africa were analyzed: maize, sorghum, millets, potato, common bean, and banana. Maize, sorghum and millets all provide >100 kcal/capita/day on average across Africa based on 2008 data (FAO, 2010), and with the exception of wheat (principally imported) and sugar cane are the primary providers of dietary energy (FAO, 2010). Potato, common bean and banana are of significant importance in specific regions, playing a role in nutritional security, and also benefit from having published parameters for the EcoCrop model employed in this research (Beebe et al., 2011; Ceballos et al., 2011; Ramirez et al., 2011; Schafleitner et al., 2011). One advantage of using EcoCrop is the relative ease in parameterization for different crops (Sect. 2.4) and the good performance for predicting climatic suitability and crop distribution even when using the default parameters reported in the FAO-EcoCrop database (FAO, 2000; Ramirez-Villegas et al., 2011). The accuracy of the approach increases when calibrated parameter sets are used, as in this case (Table 3) (Ramirez-Villegas et al., 2011). The same impact metrics as for cassava (Sect. 2.4) were calculated for these crops.

The average change of all these crops was calculated to map the impacts for comparison with cassava. The map was constructed to illustrate: (1) areas where cassava increases and the other crop(s) lose suitability, (2) areas where cassava decreases and the other crop(s) increase suitability, (3) areas where both decrease suitability, (4) areas where both increase suitability.

2.6. Impacts on pests and diseases

Here we build upon the species distributions models developed by Herrera Campo et al. (2011) and subsequently generated data on cassava mealybug (CMB, *Phenacoccus manihoti* M-F., Hemiptera: pseudococcidae), and project these onto future scenarios for the year 2030. Herrera Campo et al. (2011) assessed the predictive skill of different species distributions modeling techniques using presence-only cassava pest and disease records from the International Center for Tropical Agriculture (CIAT) virology and entomology units and from other secondary information sources. Models included Maxent (Phillips et al., 2006), GARP (Genetic

Algorithm for Rule-set Production) (Anderson et al., 2003), support vector machines (Drake et al., 2006), among others. GARP and Environmental Distance, in conjunction with expert-selected environmental predictors from WCL-BC, were found to have the most consistent performance (Herrera Campo et al., 2011), and so are used for the present investigation.

As models were driven by WCL-BC in the original study of Herrera Campo et al. (2011), pest and disease predictions for current conditions were extracted for Africa from the original study (Sect. 2.1). The parameterized model was then used to project the species distributions of whitefly (*Bemicia tabaci* G., Hemiptera: Aleyrodidae), cassava mealybug (CMB, *Phenacoccus manihoti* M-F., Hemiptera: pseudococcidae) cassava mosaic disease (CMD, c*assava mosaic geminiviruses*: Geminiviridae), and cassava brown streak disease (CBSD, *cassava brown streak virus*: Potyviridae) onto the ENS-BC future projection (Sect. 2.2.2). With the projected pest and disease models we calculated the changes in suitability for each biotic constraint on a pixel basis and mapped them using R-2.13.2 (R Development Core Team, 2011). The following metrics were calculated for each biotic factor at regional and national levels:

(a) overall change in suitability in percentage (OSC),
(b) amount of area that becomes unsuitable (i.e. reduces below 70% suitability),
(c) amount of area that expands (i.e. increases above 70% suitability).

2.7. Abiotic breeding priorities

EcoCrop uses adaptation ranges of crops to describe crop responses to environmental stresses, and therefore it is possible to parameterize the model to explore the sensitivities to variations in marginal and optimal adaptation thresholds. Shifting the adaptation ranges of the crop to simulate possible scenarios of crop improvement (e.g. a new cassava variety with greater tolerance to heat) results in different suitability predictions and permits the quantification of possible benefits of such a variety. Unfortunately, the underlying genetic traits of the crops is difficult to relate with the results of the model (Ramirez-Villegas et al., 2011), an issue also present in other crop models (Boote et al., 1996, 2001).

Ceballos et al. (2011), following the method of Beebe et al. (2011) used EcoCrop to explore the likely improvement in the response of cassava under future scenarios when broadening the optimal adaptation range of the crop. The method consists in altering the original optimal parameter set (T_{OPMIN}, T_{OPMAX}, R_{OPMIN}, and R_{OPMAX}) one parameter at a time within a range using equal steps (i.e. a Monte-Carlo approach). The new suitability of the crop under future conditions is then calculated to determine the degree at which these hypothetical improved crop parameters (reflecting an improved crop) can reduce negative impacts or even further improve the crop response in environments where it is not suited at all. We performed the analyses separately for precipitation and temperatures as described below:

(a) temperature-resilience scenarios reflect the effect of heat and cold tolerance in the crop, and were assessed by modifying the minimum and maximum optimum crop suitability temperature thresholds (T_{OPMIN}, T_{OPMAX}) five times using an incremental step of 0.5°C.
(b) rainfall-resilience scenarios reflect the effect of waterlogging and drought tolerance in the crop and were assessed by modifying the minimum and maximum optimum crop suitability thresholds (R_{OPMIN}, R_{OPMAX}) five times using an incremental step of 5%.

Model runs using these altered parameter sets (Table 4) were summarized onto a map indicating the parameter producing the largest reduction of negative impacts or the largest increase in positive impact and a graph showing the percentage increase in highly suitable (>80%) areas (including possible cropland expansion).

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Table 4 Artificial modifications to the cassava model reflecting breeding scenarios

Altered parameter	Modification[1]					Step
	1	2	3	4	5	
TOPMIN	22.0	21.5	21.0	20.5	20.0	0.5°C
TOPMAX	32.5	33.0	33.5	34.0	34.5	0.5°C
ROPMIN	760	722	686	652	619	5%
ROPMAX	2310	2426	2547	2674	2808	5%

[1] Each parameter modification is done separately at a time keeping all other parameters in the model as reported in Table 2.

3. Results and Discussion

3.1. Projected climatic changes for cassava growing regions

Changes in climate as projected by the 24 GCMs (Table 2, Sect. 2.2.2) under the SRES-A1B emissions scenario showed that by 2030, predicted increases in temperatures range between 1.2 and 2°C (Figure 1A), with North Africa (NAF) and the Sahel (SAH) showing the largest increases (80% countries with increases above 1.5°C), followed by Southern Africa (SAF), where seasonal temperatures (i.e. summer periods) are predicted to have the largest increases (data not shown). Western Africa (WAF), East Africa (EAF) and Central Africa (CAF), where most cassava production is located (>90%, data not shown) are predicted with the least regional increases (>70% countries with increases below 1.5°C) (Figure 1A). Moreover, the countries with greatest production show the least increases in temperatures (Table 6), an issue not found for other crops (Asseng et al., 2004; Challinor et al., 2007; Lobell et al., 2008; Schlenker and Lobell, 2010), although these increases were never less than 1.2°C (Table 6). Nevertheless, the implications of excessively higher temperatures (+1.5°C) in areas where cassava is grown could substantially impact production (El-Sharkawy, 2004) (see Sect. 3.2).

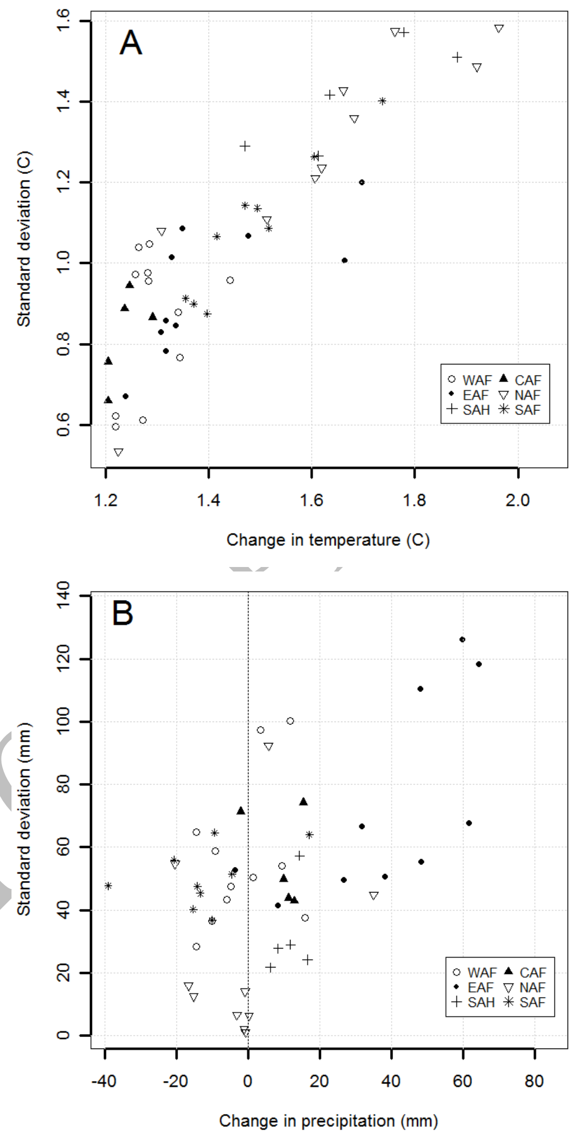

Figure 1 Predicted changes in climates as averages of 24 GCMs (Table 2) and uncertainties expressed as standard deviations of the GCMs. (A) Annual mean temperature, (B) total annual rainfall. Zone typology as in Figure S1.

Uncertainties in temperature predictions, as expressed by standard deviations among GCMs were never below 0.5°C, indicating relatively strong disagreement in GCM signals even for temperature, an issue already reported in the literature (Majda and Gershgorin, 2010; Matsueda and Palmer, 2011; Neelin et al., 2006; Pierce et al., 2009). Nevertheless, uncertainties in temperatures were observed comparatively low (<0.7°C) only in Gabon (0.66°C), Madagascar (0.67°C), Equatorial Guinea (0.53°C), Guinea-Bissau (0.61°C), Liberia (0.6°C), and Sierra

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Leone (0.62°C), whereas the largest variation among GCMs (>1.5°C) was observed in Mauritania (1.58°C), Western Sahara (1.57°C), Mali (1.51°C), and Niger (1.57°C), although in no cases the standard deviation exceeded the predicted change (Figure 1A). No GCM predicts that temperatures remain stable or reduce.

Predicted changes in precipitation ranged between -39 to +64 mm/year (Figure 1B), with most countries in East Africa (EAF) showing increases in rainfall in the range of 20-60 mm/year, whilst most countries in North Africa (NAF) and South Africa (SAF) showed decreases mostly not larger than 20 mm/year (i.e. greatest rainfall decrease was predicted for Zimbabwe [-40 mm/year]) (Figure 1B). The 24 GCMs used here also showed that on average varying rainfall responses are predicted in countries of West Africa (WAF), with some countries increasing yearly rainfall: Benin (9.4±54), Liberia (3.3±97.4), Nigeria (15.8±37.6), Sierra Leone (11.6±100.2), and Togo (1.3±50.4), and others decreasing: Ivory Coast (-14.6±64.9), Gambia (-10.1±36.4), Ghana (-6±43.3), Guinea (-9.2±58.7), Guinea-Bissau (-4.9±47.6), and Senegal (-14.5±28.3), although uncertainty related to GCMs was high. An overall increase in yearly rainfall in the Sahel (SAH) between 6-18 mm/year is predicted (Figure 1B).

3.2. Impacts on cassava climate suitability

Based on these projected changes in climate, the resultant changes in cassava climatic suitability as predicted by the EcoCrop model indicates increases in the majority of areas (5.5 million km^2 of positively impacted areas vs. 3.3 million km^2 of negatively impacted areas), although this varies depending on the GCM used (Figure 2, Table 5). EAF and SAF showed the largest increases in climatic suitability overall (20-60%), whereas the Sahel presented moderate increases (1-10%), and Central Africa (CAF) and WAF presented the decreases, although these were modest (-1 to -20%). Very importantly, increases in cassava suitability seem to occur in a greater proportion over currently cropped areas (You et al., 2009) (Figure 2A). Variation amongst individual GCM predictions was significant and predicted impacts with very high certainty (>80% GCMs predicting changes in the same direction, Figure 2D) were only found in CAF, western WAF and the mid- and high-lands of EAF (Figure 2D, Figure 3). These differences can also be observed in the difference between "optimistic" (i.e. 25th highest) GCMs and "pessimistic" (i.e. 25th lowest) predictions (Figure 2B, 2C). In the Sahel, for instance, where the optimistic prediction shows increases (5-30%), the pessimistic prediction shows decreases (0-5%) (Figure 2B, 2C). Figures of change in suitability at the country level ranged between -3.7 (±4.71) (Mauritania) and 17.5% (±11.1) (Rwanda); nevertheless, the majority of countries (58%) were predicted to have increases in suitability (Figure 2, Table 6). These increases were located in countries where the most significant production is reported (FAO, 2010), although some decreases were observed in southern WAF (Figure 2, 3). The most severe impacts were observed in West Africa (WAF) and the Sahel (SAH), where predicted changes were negative in 82 and 80% of the countries, respectively (Table 6, Figure 3). In other sub-regions of Africa, the proportion of negatively impacted countries is far lower: EAF (0%), NAF (10%), and SAF (11.1%).

Very few studies have focused on cassava when predicting impacts of climate change on crop production, partly because process-based crop models are not accurate or not available at all (Boote et al., 2010, 1996; Challinor and Wheeler, 2008a), and partly because most research on climate change impact assessment has focused on the better documented staples maize, wheat and rice (Aggarwal and Mall, 2002; Bakker et al., 2005; Jamieson et al., 2000; Jones and Thornton, 2003). Here we have found that by 2030 (1) major decreases in cassava climatic suitability are not expected for the majority of areas in Africa, and (2) increases in suitability could occur, although this depends on the GCM ensemble used. The implications of these conclusions agree with those of Kamukondiwa (Kamukondiwa, 1996) and other authors that have reported the beneficial characteristics and resilience of cassava (El-Sharkawy and Cock, 1987; El-Sharkawy et al.,

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1992; Fermont et al., 2009) in the context of climate change.

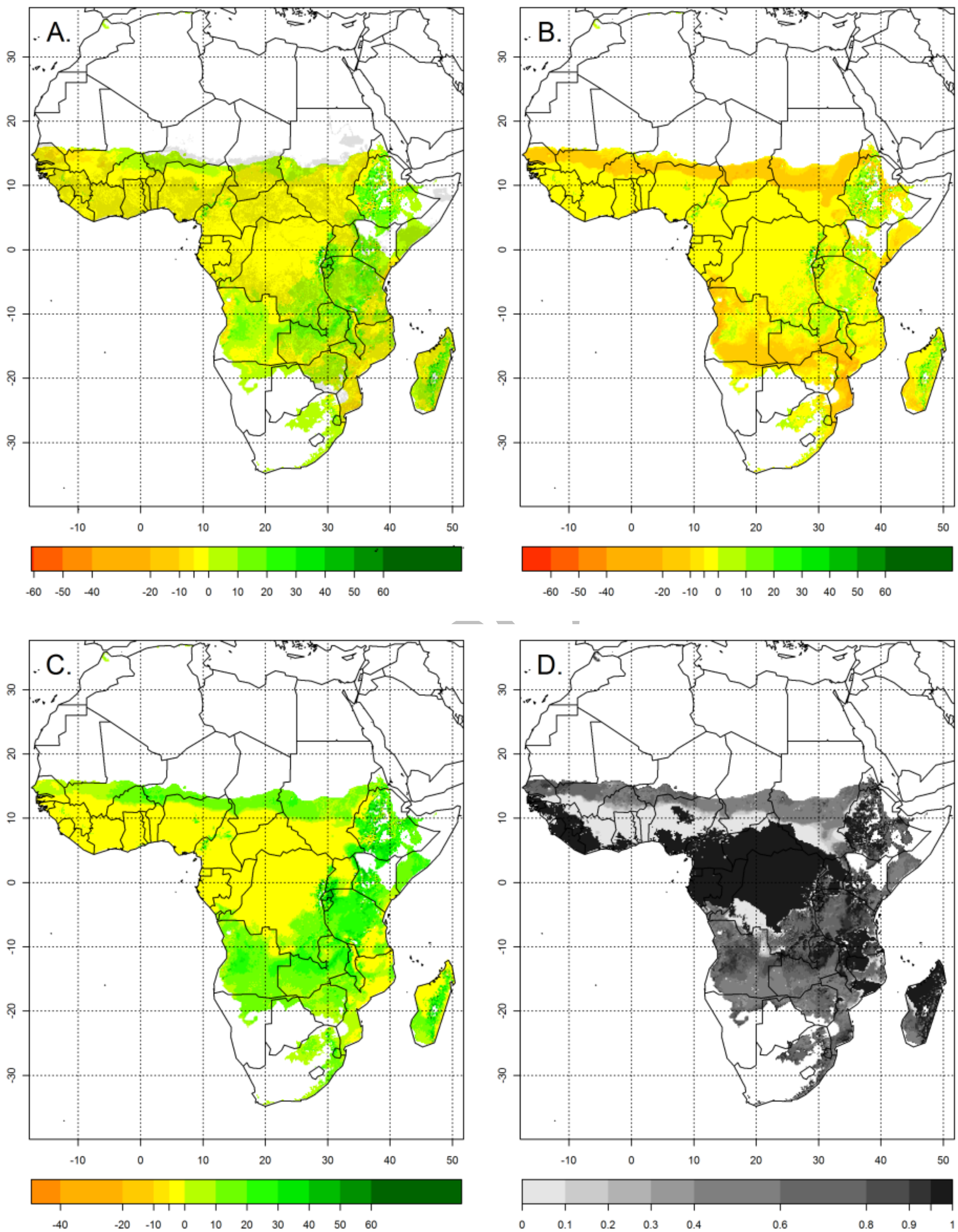

Figure 2 Predicted changes in cassava suitability and corresponding uncertainties. (A) Change in suitability as average of the 24 GCMs overlaid with croplands (grey shade) as reported in You et al. (You et al., 2009), (B) average of the first quartile of GCMs, (C) average of the 3rd quartile of GCMs, and (D) fraction of GCMs agreeing in suitability change prediction.

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Table 5 Regional changes in cassava suitability for individual GCMs

GCM	OSC[1] (%)	SCPIA[1] (%)	PIA[1] ($km^2 \times 10^6$)	PPIA[1] (%)	SCPNA[1] (%)	PNA[1] ($km^2 \times 10^6$)	PPNA[1] (%)
BCCR-BCM2.0	1.99	9.10	5.71	35.39	-6.54	3.08	19.10
CCCMA-CGCM3.1-T47	3.39	12.29	6.14	38.07	-7.98	2.65	16.44
CCCMA-CGCM3.1-T63	4.73	14.81	6.36	39.47	-7.40	2.52	15.61
CNRM-CM3.0	4.66	11.28	7.41	45.97	-6.78	1.30	8.06
CSIRO-MK3.0	1.46	9.40	5.21	32.29	-7.36	3.44	21.36
CSIRO-MK3.5	1.15	11.95	4.72	29.27	-8.57	4.41	27.33
GFDL-CM2.0	0.62	11.49	4.06	25.19	-7.61	4.77	29.59
GFDL-CM2.1	0.05	11.79	4.51	28.00	-11.16	4.69	29.11
GISS-AOM	2.42	8.34	6.05	37.51	-4.97	2.28	14.11
GISS-MODEL-EH	5.15	12.06	7.43	46.08	-5.55	1.29	8.00
GISS-MODEL-ER	1.71	9.37	5.15	31.93	-5.87	3.59	22.27
IAP-FGOALS1.0-G	-1.10	8.52	3.33	20.64	-8.16	5.61	34.81
INGV-ECHAM4	-0.72	7.37	3.47	21.50	-7.02	5.25	32.55
INM-CM3.0	3.24	11.78	5.95	36.91	-6.56	2.68	16.65
IPSL-CM4	3.65	9.94	6.55	40.63	-3.72	1.75	10.82
MIROC3.2-HIRES	5.81	16.10	6.69	41.47	-6.59	2.11	13.09
MIROC3.2-MEDRES	7.49	16.60	7.66	47.53	-6.50	1.09	6.77
MIUB-ECHO-G	3.58	9.11	7.28	45.16	-6.11	1.52	9.42
MPI-ECHAM5	1.26	6.84	5.34	33.12	-5.13	3.11	19.29
MRI-GCGM2.3.2A	0.77	8.19	4.45	27.59	-6.03	3.98	24.70
NCAR-CCSM3.0	5.52	12.95	7.50	46.51	-6.75	1.30	8.06
NCAR-PCM1	0.23	17.46	4.74	29.41	-12.81	6.19	38.40
UKMO-HadCM3	-1.47	10.36	3.43	21.28	-10.26	5.75	35.68
UKMO-HadGEM1	-0.05	11.28	4.21	26.11	-9.76	4.87	30.23

[1]OSC: overall suitability change; SCPIA: suitability change in positively impacted areas; PIA: positively impacted areas; PPIA: percent of positively impacted areas; SCNIA: suitability change in negatively impacted areas; NIA: negatively impacted areas; PNIA: percent of negatively impacted areas. The sum of PPIA and PPNA does not account to 100% because there are areas where the crop is 100% suitable both presently and in the future.

Cassava physiology, despite being complex, is well documented (Cock et al., 1979; El-Sharkawy and Cock, 1987; El-Sharkawy, 2004). Cassava grows optimally in the range 25-29°C (Ceballos et al., 2011; Edwards et al., 1990; El-Sharkawy, 2004; El-Sharkawy et al., 1992), although it can stand temperatures of up to 38°C (Cock et al., 1979). Low temperatures inhibit plant growth and reduce leaf production rate, biomass and roots yield (<15°C and <17°C, respectively) but rarely kill the plant (Cock et al., 1979; El-Sharkawy, 2004; Fermont et al., 2009). Temperatures above the optimal (i.e. between 30-40°C) have been reported to increase photosynthetic rates and faster branching (Cock et al., 1979; Edwards et al., 1990; El-Sharkawy, 2004). Moreover, decreases in root yield are very little or non-existent when the optimal range is exceeded even by 5-10°C (Cock et al., 1979; El-Sharkawy et al., 1984; Fermont et al., 2009). Therefore, tolerance to high temperatures in cassava is well known and documented (Ceballos et al., 2011; Cock et al., 1979; El-Sharkawy, 2004; El-Sharkawy et al., 1992;

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Fermont et al., 2009). The crop is also tolerant to within-season drought, although this depends on the timing, strength and duration. Prolonged periods of drought can cause root yield decreases of up 32-60% if these stress periods are prolonged enough (>2 months) and occur at the root thickening initiation stage (Cock et al., 1979; Connor et al., 1981; El-Sharkawy and Cock, 1987; El-Sharkawy et al., 1992). The effects of current drought periods in areas of the Sahelian belt are unlikely to be exacerbated by the yearly and seasonal rainfall predicted by 2030 (Figure 1, 2). Cassava has no critical period in its growth cycle once it is established, which contrasts with crops such as maize with anthesis stress causing crop failure. Hence cassava is not only tolerant of drought but also of erratic or uncertain rainfall patterns. It is therefore reasonable to expect that under a changing climate of increasing temperatures and likely more erratic and increased or decreased rainfall (depending upon the region), these favorable characteristics of the crop facilitate adaptation to future climates through favorable crop responses. However, the combination of temperature increases, changes in rainfall, increased CO_2, varying prevalence of pests and diseases needs to be analyzed holistically (Ceballos et al., 2011). Responses of the cassava plant to all stresses and CO_2 fertilization effects together can interact and offset one each other and cause unexpected responses in cropping systems (Cock et al., 1979; El-Sharkawy, 2004; Fermont et al., 2009).

Our conclusions are based on the effects of climatic niche displacement on the crop, rather than on the specific physiologically modeled responses to specific stresses and hence should be interpreted with caution (Ramirez-Villegas et al., 2011). There is, however, a relationship (not established in this study) between EcoCrop's climatic suitability rating and yields (Ramirez-Villegas et al., 2011), although such a signal is difficult to isolate due to the influence of other factors on yields, the lack of consistently measured yield data and the lack of detail in EcoCrop (Ramirez-Villegas et al., 2011). Additionally, our results agree with other published estimates of the response of cassava to changes in climates (Lobell et al., 2008; Schlenker and Lobell, 2010) (not shown).

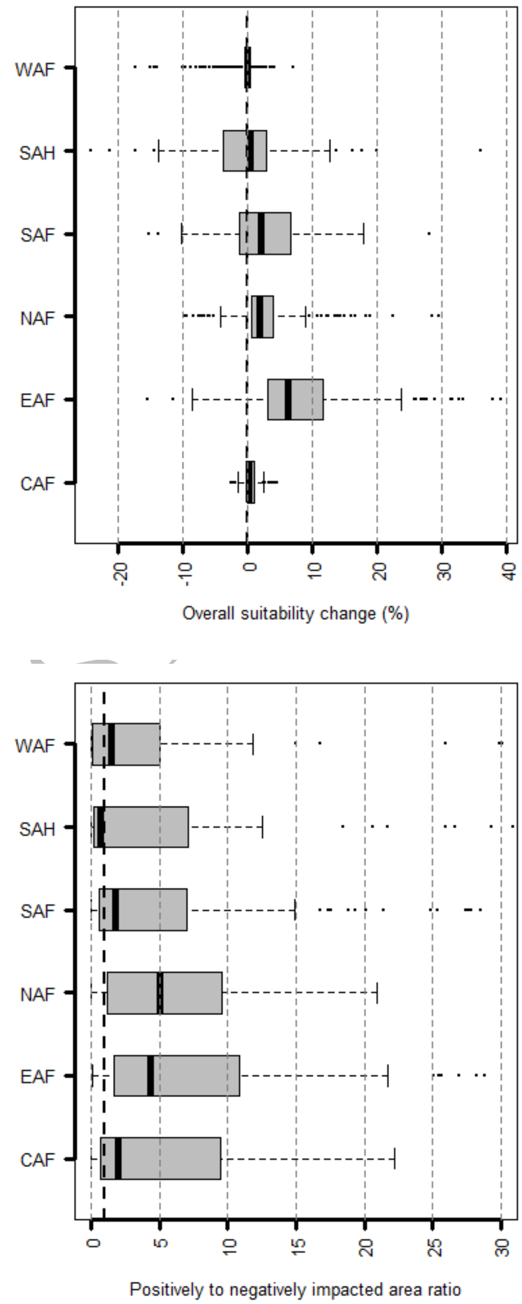

Figure 3 Impacts of climate change on cassava suitability in sub-regions of Africa. (A) Average change in suitability, (B) ratio of positively to negatively impacted areas (values above 1 indicate that positively impacted areas are larger than those negatively impacted. The distributions of boxplots are combinations of GCM-by-country predictions. Thick black vertical lines are the median, boxes show the first and third quartile and whiskers extend 5% and 95% of the distributions. Zone typology is provided in Figure S1.

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3.3. Impacts on other staple crops

Whilst cassava growth and development may be favoured by climate change, we found varying patterns of response in the additional crops analyzed (maize, sorghum, millet, beans, potato, and banana) Figure 4 shows the projected changes in crop suitability for each region and the associated uncertainties. In WAF, large negative impacts were predicted for potato (-15%, high certainty), beans (-20%, intermediate certainty), and banana (-13%, intermediate certainty), whereas millet, maize and cassava were predicted to remain the same. Sorghum showed positive impacts (10%, high certainty) in this region. In EAF, however, cassava showed the greatest potential compared to all other crops (10%), whereas beans and potatoes were the most affected. In SAH, responses were similar to those found in WAF, whereas responses in SAF were observed positive only for cassava, millet and banana (5% each). In CAF, there were very little increases (<1% for all crops except potato and beans, that were predicted with a substantial decrease). Uncertainties were highly significant for beans, potato and maize in SAF, all crops except sorghum in EAF, maize, beans and potato in NAF, and maize and cassava in SAH.

Contrasting responses were found between cassava and sorghum; increases in sorghum suitability were often related with decreases in cassava regardless of the sub-region in Africa. Potato and beans presented fairly similar sensitivities, probably due to their climatic niche similarity in highland areas (Agtunong et al., 1992; Gutíerrez et al., 1994; Schafleitner et al., 2011), although potato was found to be more sensitive. Generally, cassava reacted very well to the predicted future climate conditions compared to other crops, with some exceptions (i.e. sorghum in West Africa and the Sahel). The resilience of cassava compared to other crop plants was evidenced in the results of the modeling carried out here (Figure 5A) (Cock et al., 1979; El-Sharkawy and Cock, 1987; El-Sharkawy et al., 1992; Kamukondiwa, 1996). Whilst most areas in Africa were predicted to experience decreases in overall suitability of the additional crops modeled (Figure 6), cassava always outperformed or (in the worst case) equaled the average and the worst of these crops (Figure 5B, 5D). Areas where cassava is outperformed can only be observed when the best of the other crops is compared with cassava (Figure 5C) and even then cassava can still be grown without major restrictions (i.e. future suitability >80%).

Table 6 Cassava harvested area, total cassava production and predicted impacts of climate change on climatic suitability of cassava and four major pests in Africa

Country	HA[1] (ha x 10^6)	TP[1] (ton x 10^6)	TC[1] (°C ± SD)	PC[1] (mm ± SD)	OSC[1] (% ± SD)	Ratio[1] (± SD)	*B. tabaci* OSC[1] (%)	*B. tabaci* ES[1] ratio	BSV[3] OSC[1] (%)	BSV[3] ES[1] ratio	CMD[3] OSC[1] (%)	CMD[3] ES[1] ratio	*P. manihoti* OSC[1] (%)	*P. manihoti* ES[1] ratio
Nigeria	3.13	36.80	1.3 (±1)	15.8 (±37.6)	0.2 (±3.2)	1.2 (±0.6)	-5.8	0.1	-3.9	Inf[4]	-12.3	0.1	-21.7	0.0
DRC[2]	1.85	15.00	1.2 (±0.8)	-2.1 (±71.3)	-0.1 (±0.7)	0.7 (±0.8)	-8.8	0.5	2.0	1.2	-8.2	0.3	11.5	4.1
Tanzania	1.08	5.92	1.3 (±0.8)	48.2 (±55.3)	8.3 (±5.5)	5.1 (±1)	-23.8	0.0	-27.4	0.0	-32.3	0.0	-9.2	0.1
Mozambique	1.07	5.67	1.4 (±0.9)	-13.4 (±45.3)	-0.6 (±4)	0.9 (±0.8)	-20.5	0.1	-19.7	0.1	-25.0	0.0	-5.9	0.2
Angola	0.99	12.83	1.4 (±0.9)	-20.7 (±55.9)	3.1 (±6.6)	1.8 (±0.9)	-4.1	0.5	-2.1	1.0	-2.5	0.2	1.8	2.8
Ghana	0.89	12.23	1.3 (±1)	-6 (±43.3)	-0.6 (±2.9)	0.1 (±0)	-8.9	0.0	-9.4	0.4	-18.4	0.0	-20.2	0.0
Uganda	0.41	5.18	1.3 (±0.9)	64.3 (±118.4)	4.7 (±3.2)	4.6 (±0.9)	-14.2	0.0	3.4	0.9	-17.0	0.1	-0.4	0.1
Madagascar	0.40	2.70	1.2 (±0.7)	-3.7 (±52.8)	5.6 (±2.7)	3.5 (±0.9)	-5.5	1.0	4.3	Inf	-3.6	0.4	-0.1	0.8
Ivory Coast	0.34	2.90	1.3 (±1)	-14.6 (±64.9)	-0.3 (±1.5)	0.1 (±0)	-2.0	7.0	-6.5	Inf	-15.5	1.7	-23.0	0.0

[1] HA: harvested area, TP: total production, TC: mean change and standard deviation (SD) in annual mean temperature, PC: mean change and standard deviation in total annual rainfall, OSC: overall suitability change, Ratio: ratio of amount of positively impacted areas to negatively impacted areas, ES: ratio of expansion to shrinkage of niche.

[2] Democratic Republic of Congo

[3] BSV: cassava brown streak virus; CMD: cassava mosaic disease

[4] "Inf" occurs when expansion is greater than zero and shrinkage is zero

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Cassava appears as a highly resilient staple crop, contributing to a large amount of the dietary intake of African farmers and, on top of that, it seems to respond fairly well to the projected 2030 climate (Figure 2, 3, 4), in contrast to other staples of dietary importance to Africa.

Incorporating these predictions in the food security debate entails an appropriate interpretation of them (Ramirez-Villegas et al., 2011). EcoCrop is a niche-based approach (Sect. 2.4) and as such, it is difficult to relate its outcomes with actual agricultural yields; hence, predictions cannot be taken as direct impacts on production. This makes it complicated when trying to develop adaptation options, since there are many other factors other than climates that exert control on crop production, some of which have not been studied properly or are difficult to measure and monitor (Fermont et al., 2009; Wilby et al., 2009).

The agreement of our impact predictions with those reported in other studies is high for all crops except maize. We found strong agreement for sorghum (Ramirez-Villegas et al., 2011), potato, cassava, millets and beans future impact predictions (Hijmans, 2003; Lobell et al., 2008; Schlenker and Lobell, 2010). Results for banana are not available in the literature making comparison impossible, but the model used here was expert-evaluated (D. Turner, pers. comm.). The maize parameterization was found to be excessively broad, likely to it being based on photosynthesis and phenology parameters of plot-scale process-based models (Jones et al., 2003).

Estimates of climate change impacts on maize are varied. Fischer et al. (2001) showed that maize yields do not have a strong response in West Africa (WAF) in relation to a decrease in rainfall, whereas Roudier et al. (2011), reported decreases between -2.5 and -5% in yields by 2050 (SRES-A2). Much more severe estimates of impacts for this crop were predicted by Jones and Thornton (Jones and Thornton, 2003), who found that some 60% of the areas in East Africa are subjected to yield decreases between -5 and -20%, with severe impacts in other regions also predicted; Central Africa (-13%), Southern Africa (-16%), West Africa (-23%) (Liu et al., 2008; Thornton et al., 2011). Lobell et al. (2008) and Schlenker and Lobell (2010) also report substantial decreases in maize crop yields throughout Africa, and particularly in Southern Africa (SAF), where our predictions show a highly uncertain response with median at zero change.

Apart from the maize parameterization issue, EcoCrop also suffers from a lack of detail in representing certain processes (Sect. 2.4). Ramirez-Villegas et al. (2011) thoroughly discussed the limitations of the model. In brief, pests, diseases, soil conditions, and extreme events are not considered by the model. These factors need to be taken into account in impact assessment, although future projections on these are scarce or too uncertain (Battisti and Naylor, 2009; Garrett et al., 2009). Hence, there is a trade-off between the level of detail and uncertainty propagation (Challinor and Wheeler, 2008a; Jarvis et al., 2011). Furthermore, there are processes that need to be taken into account. For instance, the well documented effect of increased CO_2 concentrations on photosynthesis is not well represented in crop models (and not at all in EcoCrop) (Asseng et al., 2004; Fuhrer, 2003): many crop models do not properly account to the offset of CO_2 fertilization under heat stress, a combination very likely to happen with global warming (IPCC, 2007). This is particularly true for grain legumes (Boote et al., 2005; Fuhrer, 2003; Leakey et al., 2009; Prasad et al., 2002). Ways of coupling regional models such as EcoCrop (Ramirez-Villegas et al., 2011) or large-area process-based models (Challinor et al., 2004; Tao et al., 2009) with detailed field-scale crop models need to be explored so that the representation of some processes can be improved.

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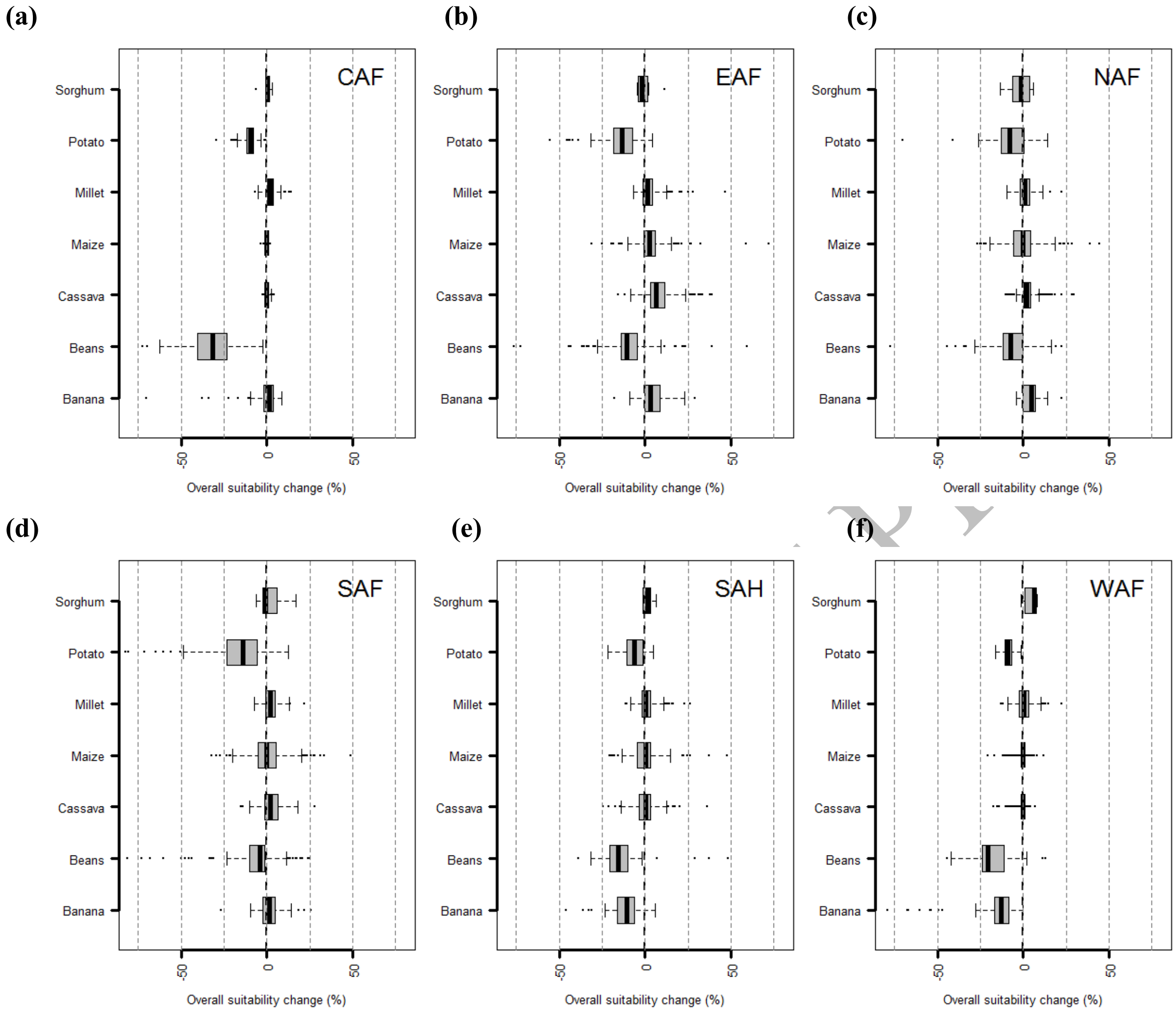

Figure 4 Impacts of climate change on other African staple crops as shown by the overall suitability change for each sub-region of Africa. The distributions of boxplots are combinations of GCM-by-country predictions. Thick black vertical lines are the median, boxes show the first and third quartile and whiskers extend 5% and 95% of the distributions. Zone typology is provided in Figure S1.

3.4. Impacts on pests and diseases

The impacts of climate change on the distribution of the four pests and diseases studied here are presented in Table 6 for the top 10 cassava producing countries, and are mapped out in Figure 6. Whitefly is the most widely distributed pest under current conditions, potentially covering 24 million km^2, but its distribution is predicted to shrink in 2030 to 22.5 million km^2, with an overall suitability change of 5.5%. However, this includes an expansion of whitefly into 600 million km^2 where the species is currently not present, accompanied by 2.1 million km^2 of area where whitefly is likely to migrate out of. The countries with the greatest increases in potential whitefly distribution are Central African Republic (120,000 km^2 new affected area), Ethiopia (97,000 km^2 new affected area) and Cameroon (45,000 km^2 new affected areas).

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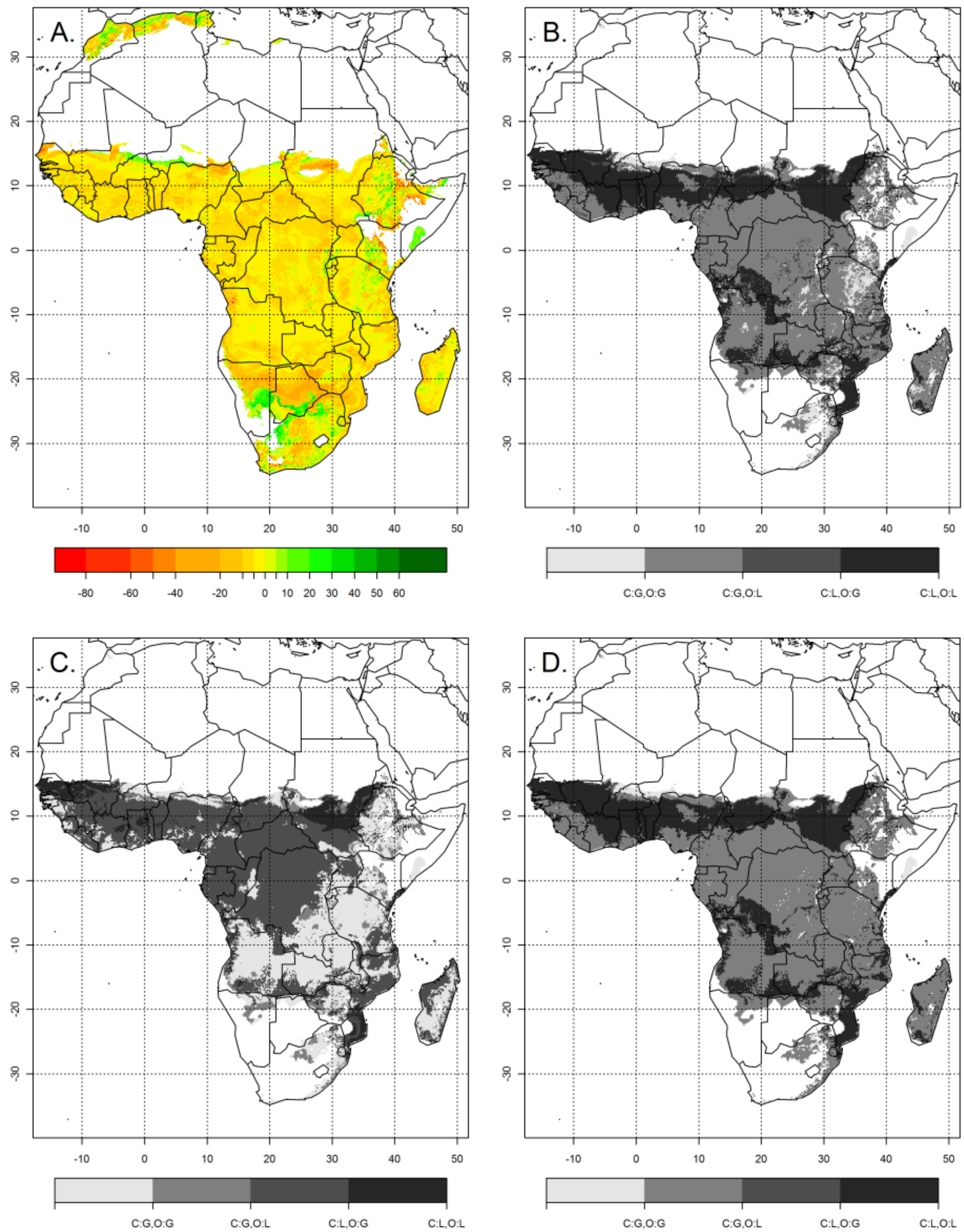

Figure 5 Changes in suitability of other staples as compared to cassava. (A) Average change in climatic suitability of the 6 other crops (i.e. among crops and GCMs), (B) discrimination of areas according to gains and losses using the mean change in suitability of all crops but cassava, (C) same as (B) but using the maximum change among the crops, and (D) same as (B) but using the minimum change among the crops. Area shading typology is C: cassava, O: other crops; G: increase in suitability, L:

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decrease in suitability. For instance, "C:G, O:L" indicates that in that area cassava (C) increases in suitability (G), and all other crops in average (O) decrease suitability (L).

For cassava brown streak disease, there are currently 15.1 million km^2 with suitable climate conditions for the pathogen across the continent, and this is predicted to decrease by 550,000 km^2 by 2030, with 250,000 km^2 of newly affected regions, and 800,000 km^2 of area which will potentially become brown streak mosaic virus free. The overall suitability for brown streak mosaic virus reduces by 1.5% across the continent, with notable increases in Democratic Republic of Congo (2%), Uganda (3.4%), Cameroon (11%), Central African Republic (16%) and Liberia (16.8%). Countries set to gain most from the changes in distribution are Tanzania (340,000 km^2 losing significant amount of climate suitability), Mozambique (180,000 km^2), and Republic of Congo (130,000km^2).

For cassava mosaic disease, there are currently 20.5 million km^2 with suitable climate conditions (based on the ecological niche 95% training presence threshold) for the pathogen across the continent, and this is predicted to decrease by 1.3 million km^2 by 2030, with 420,000 km^2 of newly affected regions, and 1.7 million km^2 of area which will potentially become free of the pathogen (Figure 6c). The overall suitability for cassava mosaic disease reduces by some 8% across the continent, with increases only in a handful of countries; Central African Republic (5.5%), Liberia (1.7%) and Equatorial Guinea (10.1%). Countries set to gain most from the changes in distribution are Tanzania (397,000 km^2 losing significant amount of climate suitability), Republic of Congo (380,000 km^2) and Mozambique (350,000 km^2).

Cassava mosaic disease represents one of the primary constraints to cassava production in Africa (Patil and Fauquet, 2009; Thresh et al., 1998). The only alternative for its control is with host plant resistance, appropriate crop management, and through management of the vector (*Bemisia tabaci*). Two particularly aggressive strains can produce mixed infestations in the crop, making its management highly complex (Mbanzibwa et al., 2011; Monger et al., 2010). With climate change, and the predicted shift in geographic distributions this could bring into contact multiple strains which previously have not been in contact, causing more virulent strains and contributing to greater losses.

For mealybug, there are currently 19.1 million km^2 with suitable climate conditions for the species across the continent, and this is predicted to decrease by 700 million km^2 by 2030, with 1 million km^2 of newly affected regions, and 1.8 million km^2 of area which will potentially become free of the insect pest. The overall suitability for cassava mealy bug reduces by 4.5% across the continent, with important increases in some major cassava producing countries; Democratic Republic of Congo (11.5%), Central African Republic (10.3%). Countries set to gain most from the changes in distribution are Nigeria (250,000 km^2 losing significant amount of climate suitability), Ivory Coast (220,000 km^2), Zambia (210,000 km^2) and Tanzania (195,000 km^2). Cassava mealybug has been managed successfully through biological control (Neuenschwander, 2001), and so it is important that the distribution of biological control agents are also incorporated into the models to better assess the impacts on the insect pest.

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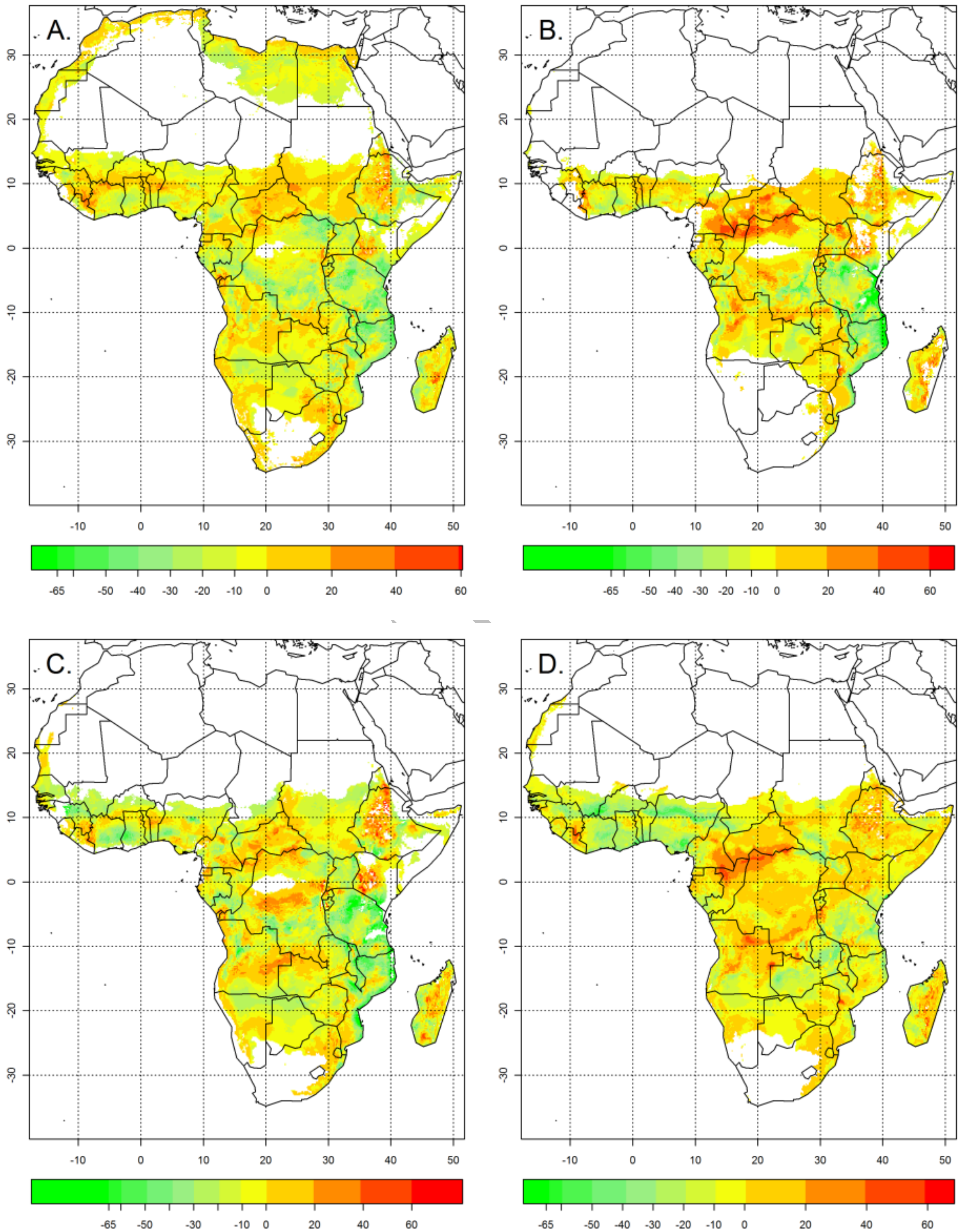

Figure 6 Predicted changes in suitability of major cassava pests and diseases. (A) Whitefly, (B) cassava brown streak virus, (C) cassava mosaic geminivirus, and (D) cassava mealybug.

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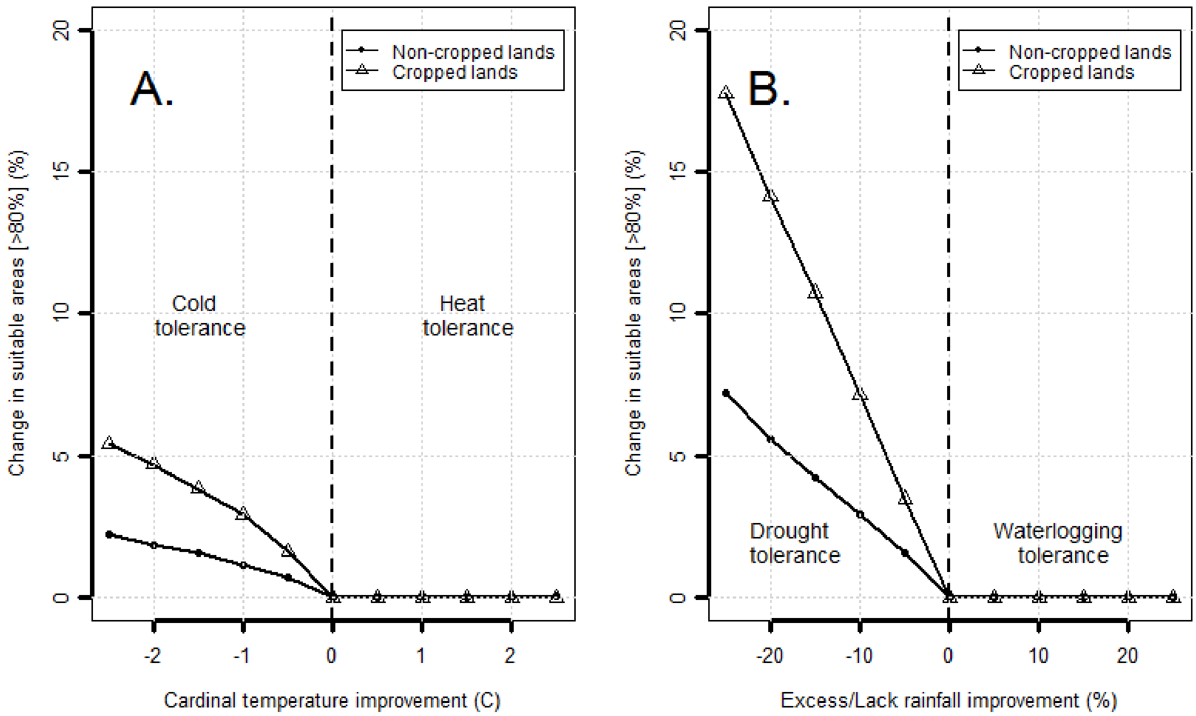

Figure 7 Potential benefits (i.e. increases of highly suitable [>80% suitability] area) from new combinations of parameters reflecting the breeding scenarios of Table 4 for (A) cold and heat tolerance, and (B) drought and waterlogging tolerance in cassava cropped and non-cropped areas of Africa.

Overall, the results indicate possible reductions in pest and disease distribution and prevalence across the continent, with notable hotspots where increases in prevalence are projected (Figure 6). However, these results should be taken with caution. First, these are based only on environmental niche based approaches, which use the present distribution of the pest or disease to train a statistical model that describes the climate conditions likely to harbor the pest or disease. The model is only as good as the data used to develop it, and hence biases in presence data may affect the result. Furthermore, the geographic distribution of these pests and diseases may not be limited by climate, but rather host plants or other biological factors; hence any shift in the geographic distribution of cassava (assessed in Sect. 3.2) may broaden the geographic and environmental range of the pest or disease. These analyses also assume zero adaptation of the pests and diseases themselves, but evidence based on the past century indicates that the rate of evolution of new pathogens is significant (Gregory et al., 2009; Patil and Fauquet, 2009; Winter et al., 2010). Hence those regions where the pest or disease is predicted to lose suitability may continue to suffer as the insect or virus evolves or adapts to the novel conditions. An important next step for research would be to combine abiotic models with biotic models, which unfortunately is not possible with the currently available models.

3.5. Abiotic breeding priorities

Figure 7 shows the fractional area of cassava producing regions and other lands that would potentially benefit under a 2030 climate from crop improvement on abiotic tolerances to drought, waterlogging, heat and cold. Regional specificities in these crop improvement priorities are shown in Figure 8. Many cassava growing regions (>80% of area) are

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not abiotically constrained in 2030, meaning that they are unlikely to benefit from crop improvement for abiotic traits. For other regions where there is an abiotic constraint, the priorities for crop improvement across the continent lie in increased drought tolerance and in cold tolerance, although these priorities do change regionally. Increased drought tolerance could bring benefits to nearly 30% of cassava producing regions in EAF, SAF and SAH. Cold tolerance is also a surprising priority in 2030 despite the projected warmer climates. This is largely because of constraints in high elevation regions of EAF (20% of cassava growing regions would benefit), or in low latitudinal regions in SAF (8% of area benefiting) where seasonal temperatures during winter pose a constraint for cassava development (Ceballos et al., 2011; Cunha Alves, 2002; El-Sharkawy, 2004). Breeding for cold tolerance in cassava is reported as being a major challenge (El-Sharkawy, 2004; Fermont et al., 2009). Low temperatures have impeded cassava expansion to temperate or Mediterranean climates, although cassava breeders have worked on it (Cunha Alves, 2002). Heat tolerance is found to only be a relevant constraint for WAF (5% of area) and SAH (2% of area).

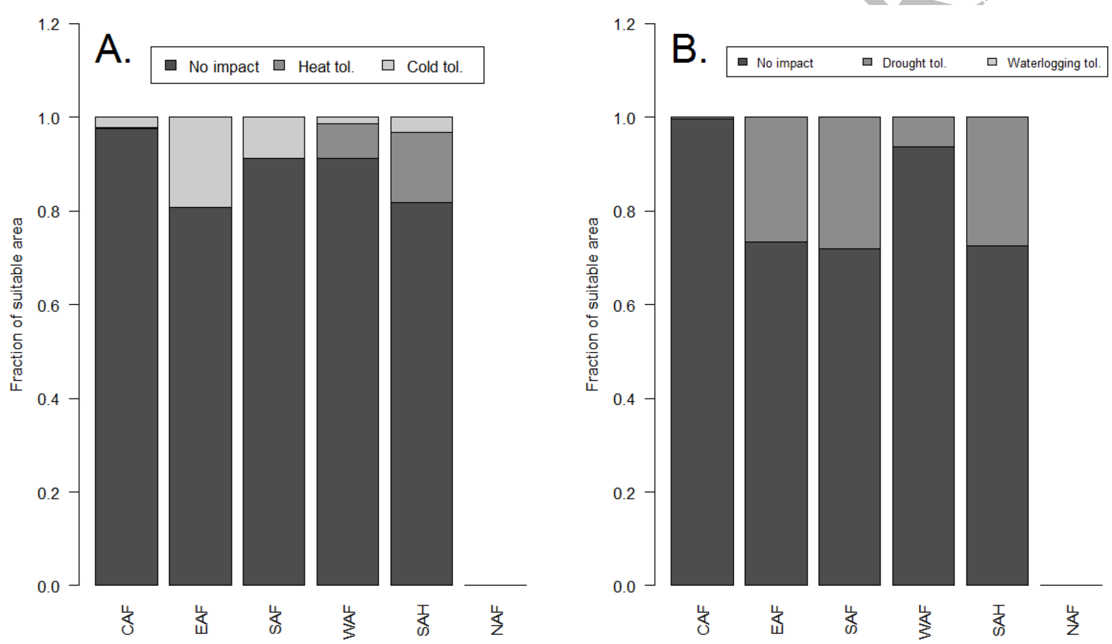

Figure 8 Predicted fractional area that would be positively impacted in each of the sub-regions of Africa (Figure S1) if the crop is improved towards (A) heat or cold tolerance, and (B) drought or waterlogging tolerance.

This analysis looks at average climate conditions during the entire cassava growing season, and does not look at within season climatic constraints which may affect the cassava crops. Nor does this look at climatic variability, such as changes in onset of rainy seasons due to alterations in Atlantic-Indian oceans sea surface temperature (SST) anomalies, the consequent change in monsoonal cycles and the El Nino Southern Oscillation (ENSO) (Douglass et al., 2008; Hulme et al., 2001; Nicholson et al., 2000). Further research should exploit the potential of mechanistic models for examining growth on a daily time step, and also permit more sophisticated scenarios for crop improvement which exploits particular physiological traits. *Ex ante* impact assessment of the benefits of biotic constraints is also a priority for further work.

3.6. Towards a 2030 cassava crop

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The combined effect of increased temperature and changing rainfall patterns (IPCC, 2007; Moss et al., 2010) is expected to not only affect crop productivity through direct stresses during key periods of plant growth, but also through impacts on soil conditions, weeds, pests and/or diseases and associated agricultural biodiversity (Jarvis et al., 2008; Jarvis et al., 2010). These changes are expected in many food crops and to a lesser extent in cassava (Figure 1) (Ceballos et al., 2011; Liu et al., 2008; Schlenker and Lobell, 2010). On the contrary, increased CO_2 concentrations are expected to stimulate more rapid growth, increase photosynthetic rates, total biomass, the harvest index, and hence yields for grain legumes and other crops (Boote et al., 2005; Challinor and Wheeler, 2008b; Fuhrer, 2003). The interaction of these two is only documented for a few crops (Leakey et al., 2009). Here, high temperatures for future cassava growth were only found to be critical in WAF (6%) and SAH (15%), whereas cool temperatures were found to play a fundamental role in the future for all other areas. A future cassava plant to be growing in high- or mid- elevation regions and in areas with strong seasonal signals needs to incorporate cold tolerance so that growth is not slowed or stopped if temperatures go below 17°C (Cunha Alves, 2002; El-Sharkawy, 2004; El-Sharkawy et al., 1984). Tolerance and/or resistance to pests and diseases are currently and will continue to be highly desirable traits for cassava varieties in the future given the geographical shifts of prevalence expected (Sect. 3.4).

Perhaps the most important abiotic factor for cassava (as shown by our analyses) was drought. Cassava is renowned for its resilience to drought, although prolonged periods during key phenological stages can decrease storage root yields (Connor et al., 1981; El-Sharkawy and Cock, 1987; El-Sharkawy et al., 1992). If the best of the crops (including cassava) is used, it is very likely that adaptation to climate change is possible through varietal change, crop rotations and crop substitution (Figure 5C) (Brown and Funk, 2008; Ceballos et al., 2011; Challinor, 2009; Gregory et al., 2005). Cassava has been shown to be a potentially useful crop for substitution as climate change impacts on other staples become greater. However, biophysical potential alone is not enough. If cassava is to support communities to adapt, a number of social, economic, institutional and cultural boundaries must be overcome, and suitable policies be put in place to facilitate the adaptation process (Challinor, 2009; Jarvis et al., 2011). Changing the staple food crop in a farming community, especially when subsistence agriculture is prevalent, has significant social and cultural implications, including gender dimensions (Barrios et al., 2008; Thornton et al., 2011). Future research should strive to better understand the conditions required for crop substitution to occur, as well as identify what agricultural know-how, technology and seed systems are required to facilitate the adaptation process. Crop substitution also has important implications for market value chains, rural institutions and broader scale food security issues (Jarvis et al., 2011; Quiggin, 2008). These complex system dynamics, although difficult to fully understand, should be evaluated more thoroughly.

4. Conclusions

This paper has aimed to update Kamukondiwa's (Kamukondiwa, 1996) argument that cassava holds great merit in supporting (southern) Africa's agricultural sector adapt to future climate change, based on the premise that the crop provides significant nutritional security to a massive population and that it is biologically resistant to stressful environments. Through modeling and quantitative data analysis, we have evaluated the impacts of climate change on cassava production, showing projected changes of –3.7% to +17.5% across the continent. This result is consistent with other studies (Liu et al., 2008; Lobell et al., 2008; Schlenker and Lobell, 2010). Differential impacts of climate change have also been shown for major staples across the continent, indicating that cassava is the least sensitive crop to a changed 2030 climate. We particularly highlight the almost opposite crop-climate responses observed between cassava and sorghum, indicating that cassava may be an important substitute crop for sorghum in areas where the latter suffers greatly. Whilst the strong abiotic resistance characteristics of cassava make the crop capable of adapting to harsher future climates, our analysis and other studies do show that the principal weakness of cassava is in terms of pest and disease sensitivity (Herrera Campo et al. 2011). Cassava experiences significant crop losses today due to biotic constraints, and future projections developed in this paper indicate that pest and disease pressure is likely to continue in many regions of Africa, moving into some new regions, as well as reducing pressure in other regions. Key priorities for research in ensuring that cassava adapts to climate change lie in increasing resistance to these key pests and diseases, as well as further developing management practices to address greater pest or disease pressure (Herrera Campo et al. 2011). Our analyses also show that improvement of abiotic resistance in cassava should focus on traits that increase resistance to drought and cold tolerance.

This paper provides a detailed quantification of climate change impacts on the cassava crop for Africa. However, there remain a number of avenues for improvement of these estimations. More research is clearly needed to understand the climate impacts on pest and disease pressure and outbreaks at a more detailed time-step than yearly. Data presented provides a preliminary analysis of impacts for four major pests/diseases for cassava in Africa based on ecological niche modeling, but mechanistic pest and disease models may be needed to further understand the complex interactions between crop, weather and pest/disease vectors and pathogens (Garrett et al., 2009), and also to assess possible adaptation responses such as those outlined by experts. Further improvement of cassava models is also of high priority. In this paper we relied on a fairly simple "niche" based model (EcoCrop), but improvement of mechanistic and process based models should be seen as a priority. This would allow not only the improved quantification of impacts, but also the evaluation of benefits of specific adaptation options at the plot scale.

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References

Aggarwal PK and Mall RK (2002) Climate Change and Rice Yields in Diverse Agro-Environments of India. II. Effect of Uncertainties in Scenarios and Crop Models on Impact Assessment. Climatic Change 52: 331-343. doi:10.1023/a:1013714506779.

Agtunong T, Redden R, Mangge-Nang M, Searle C and Fukai S (1992) Genotypic variation in response to high temperature at flowering in common bean (*Phaseolus vulgaris* L.). Australian Journal of Experimental Agriculture 32: 1135-1140. doi:http://dx.doi.org/10.1071/EA9921135.

Anderson RP, Lew D and Peterson AT (2003) Evaluating predictive models of species' distributions: criteria for selecting optimal models. Ecological Modelling 162: 211-232. doi:10.1016/s0304-3800(02)00349-6.

Asseng S, Jamieson PD, Kimball B, Pinter P, Sayre K, Bowden JW and Howden SM (2004) Simulated wheat growth affected by rising temperature, increased water deficit and elevated atmospheric CO2. Field Crops Research 85: 85-102. doi:10.1016/s0378-4290(03)00154-0.

Baigorria GA, Jones JW, Shin DW, Mishra A and Brien JJ (2007) Assessing uncertainties in crop model simulations using daily bias-corrected Regional Circulation Model outputs. Climate Research 34: 211-222. doi:10.3354/cr00703.

Bakker MM, Govers G, Ewert F, Rounsevell M and Jones R (2005) Variability in regional wheat yields as a function of climate, soil and economic variables: Assessing the risk of confounding. Agriculture, Ecosystems and Environment 110: 195-209. doi:10.1016/j.agee.2005.04.016.

Barrios S, Ouattara B and Strobl E (2008) The impact of climatic change on agricultural production: Is it different for Africa? Food Policy 33: 287-298. doi:DOI: 10.1016/j.foodpol.2008.01.003.

Battisti DS and Naylor RL (2009) Historical Warnings of Future Food Insecurity with Unprecedented Seasonal Heat. Science 323: 240-244. doi:10.1126/science.1164363.

Beebe S, Ramirez J, Jarvis A, Rao IM, Mosquera G, Bueno JM and Blair MW (2011) Chapter 16: Genetic Improvement of Common Beans and the Challenges of Climate Change. Wiley and Sons.

Boote KJ, Allen LH, Prasad PVV, Baker JT, Gesch RW, Snyder AM, Pan D and Thomas JMG (2005) Elevated Temperature and CO_2 Impacts on Pollination, Reproductive Growth, and Yield of

Several Globally Important Crops. Japanese Journal of Meteorology 60: 469-474.

Boote KJ, Jones JW, Hoogenboom G and White JW (2010) The Role of Crop Systems Simulation in Agriculture and Environment. International Journal of Agricultural and Environmental Information Systems 1: 41-54. doi:10.4018/jaeis.2010101303.

Boote KJ, Jones JW and Pickering NB (1996) Potential uses and limitations of crop models. Agronomy Journal 88: 704-716.

Boote KJ, Kropff MJ and Bindraban PS (2001) Physiology and modelling of traits in crop plants: implications for genetic improvement. Agricultural Systems 70: 395-420. doi:Doi: 10.1016/s0308-521x(01)00053-1.

Brown ME and Funk CC (2008) Food Security Under Climate Change. Science 319: 580-581. doi:10.1126/science.1154102.

Ceballos H, Ramirez J, Bellotti AC, Jarvis A and Alvarez E (2011) Chapter 19: Adaptation of Cassava to Changing Climates. Wiley and Sons.

Challinor A (2009) Towards the development of adaptation options using climate and crop yield forecasting at seasonal to multi-decadal timescales. Environmental Science and Policy 12: 453-465. doi:DOI: 10.1016/j.envsci.2008.09.008.

Challinor AJ, Osborne T, Shaffrey L, Weller H, Morse A, Wheeler T and Vidale PL (2009) Methods and Resources for Climate Impacts Research. Bulletin of the American Meteorological Society 90: 836-848. doi:doi:10.1175/2008BAMS2403.1.

Challinor AJ and Wheeler TR (2008a) Crop yield reduction in the tropics under climate change: Processes and uncertainties. Agricultural and Forest Meteorology 148: 343-356. doi:DOI: 10.1016/j.agrformet.2007.09.015.

Challinor AJ and Wheeler TR (2008b) Use of a crop model ensemble to quantify CO2 stimulation of water-stressed and well-watered crops. Agricultural and Forest Meteorology 148: 1062-1077. doi:DOI: 10.1016/j.agrformet.2008.02.006.

Challinor AJ, Wheeler TR, Craufurd PQ, Ferro CAT and Stephenson DB (2007) Adaptation of crops to climate change through genotypic responses to mean and extreme temperatures. Agriculture, Ecosystems and Environment 119: 190-204. doi:DOI: 10.1016/j.agee.2006.07.009.

Challinor AJ, Wheeler TR, Craufurd PQ, Slingo JM and Grimes DIF (2004) Design and optimisation of a large-area process-based model for annual crops. Agricultural and Forest Meteorology 124: 99-120. doi:DOI: 10.1016/j.agrformet.2004.01.002.

Cock JH, Franklin D, Sandoval G and Juri P (1979) The Ideal Cassava Plant for Maximum Yield. Crop Sci. 19: 271-279. doi:10.2135/cropsci1979.0011183X001900020025x.

Connor DJ, Cock JH and Parra GE (1981) Response of cassava to water shortage I. Growth and yield. Field Crops Research 4: 181-200. doi:10.1016/0378-4290(81)90071-x.

Cunha Alves AA (2002) Chapter 5: Cassava Botany and Physiology: Cassava: Biology, Production and Utilization (ed. by RJ Hillocks, JM Thresh and A Bellotti) CAB International.

Douglass DH, Christy JR, Pearson BD and Singer SF (2008) A comparison of tropical temperature trends with model predictions. International Journal of Climatology 28: 1693-1701. doi:10.1002/joc.1651.

Drake JM, Randin C and Guisan A (2006) Modelling ecological niches with support vector machines. Journal of Applied Ecology 43: 424-432. doi:10.1111/j.1365-2664.2006.01141.x.

Edwards GE, Sheta E, Moore Bd, Dai Z, Franceschi VR, Cheng S-H, Lin C-H and Ku MSB (1990) Photosynthetic Characteristics of Cassava (Manihot esculenta Crantz), a C3 Species with Chlorenchymatous Bundle Sheath Cells. Plant and Cell Physiology 31: 1199-1206.

El-Sharkawy M (2005) How can calibrated research-based models be improved for use as a tool in identifying genes controlling crop tolerance to environmental stresses in the era of genomics—from an experimentalist's perspective. Photosynthetica 43: 161-176. doi:10.1007/s11099-005-0030-1.

El-Sharkawy M and Cock J (1987) Response of cassava to water stress. Plant and Soil 100: 345-360. doi:10.1007/bf02370950.

El-Sharkawy M, Cock J and Hernandez A (1985) Stomatal response to air humidity and its relation to stomatal density in a wide range of warm climate species. Photosynthesis Research 7: 137-149. doi:10.1007/bf00037004.

El-Sharkawy MA (2004) Cassava biology and physiology. Plant Molecular Biology 56: 481-501. doi:10.1007/s11103-005-2270-7.

El-Sharkawy MA, Cock JH and Held AA (1984) Photosynthetic responses of cassava cultivars (*Manihot esculenta* Crantz) from different habitats to temperature. Photosynthesis Research 5: 243-250. doi:10.1007/bf00030025.

El-Sharkawy MA, De Tafur SM and Cadavid LF (1992) Potential Photosynthesis of Cassava as Affected by Growth Conditions. Crop Sci. 32: 1336-1342. doi:10.2135/cropsci1992.0011183X003200060006x.

FAO (2000) The Ecocrop database. Food and Agriculture Organization of the United Nations. Rome, Italy.

FAO (2010) FAOSTAT. Food and Agriculture Organization of the United Nations. Rome, Italy.

Fermont AM, van Asten PJA, Tittonell P, van Wijk MT and Giller KE (2009) Closing the cassava yield gap: An analysis from smallholder farms in East Africa. Field Crops Research 112: 24-36. doi:10.1016/j.fcr.2009.01.009.

Fischer G, van Velthuizen H, Shah M and Nachtergaele F (2001) Global Agro-ecological Assessment for Agriculture in the 21st Century. IASA, FAO, Vienna, Austria.

Fuhrer J (2003) Agroecosystem responses to combinations of elevated CO2, ozone, and global climate change. Agriculture, Ecosystems and Environment 97: 1-20. doi:Doi: 10.1016/s0167-8809(03)00125-7.

Garrett K, Forbes G, Pancle S, Savary S, Sparks A, Valdivia C, Cruz CV and Willocquet L (2009) Anticipating and responding to biological complexity in the effects of climate change on agriculture. IOP Conference Series: Earth and Environmental Science 6: 372007.

Gleadow RM, Evans JR, McCaffery S and Cavagnaro TR (2009) Growth and nutritive value of cassava (Manihot esculenta Cranz.) are reduced when grown in elevated CO2. Plant Biology 11: 76-82. doi:10.1111/j.1438-8677.2009.00238.x.

Gregory PJ, Ingram JSI and Brklacich M (2005) Climate change and food security. Philosophical Transactions of the Royal Society B: Biological Sciences 360: 2139-2148. doi:10.1098/rstb.2005.1745.

Gregory PJ, Johnson SN, Newton AC and Ingram JSI (2009) Integrating pests and pathogens into the climate change/food security debate. Journal of Experimental Botany 60: 2827-2838. doi:10.1093/jxb/erp080.

Gutíerrez AP, Mariot EJ, Cure JR, Riddle CSW, Ellis CK and Villacorta AM (1994) A model of bean (Phaseolus vulgaris L.) growth types I-III: Factors affecting yield. Agricultural Systems 44: 35-63. doi:10.1016/0308-521x(94)90014-7.

Herrera Campo B, Hyman G and Bellotti A (2011) Threats to cassava production: known and potential geographic distribution of four key biotic constraints. Food Security: 1-17. doi:10.1007/s12571-011-0141-4.

Hijmans R (2003) The effect of climate change on global potato production. American Journal of Potato Research 80: 271-279. doi:10.1007/bf02855363.

Hijmans RJ, Cameron SE, Parra JL, Jones PG and Jarvis A (2005) Very high resolution interpolated climate surfaces for global land areas. International Journal of Climatology 25: 1965-1978. doi:10.1002/joc.1276.

Hijmans RJ, Guarino L, Cruz M and Rojas E (2001) Computer tools for spatial analysis of plant genetic resources data: 1. DIVA-GIS. Plant Genetic Resources Newsletter 127: 15-19.

Hulme M, Doherty R, Ngara T, New M and Lister D (2001) African climate change: 1900-2100. Climate Research 17: 145-168. doi:10.3354/cr017145.

Hutchinson MF (1995) Interpolating mean rainfall using thin plate smoothing splines. International Journal of Geographical Information Systems 9: 385 - 403.

Hutchinson MF and de Hoog FR (1985) Smoothing noisy data with spline functions. Numerische Mathematik 47: 99-106.

IPCC (2000) Special Report on Emission Scenarios. IPCC, Geneva, Switzerland.

IPCC (2007) IPCC Fourth Assessment Report: Climate Change 2007 (AR4). IPCC, Geneva, Switzerland.

Jamieson PD, Berntsen J, Ewert F, Kimball BA, Olesen JE, Pinter PJ, Porter JR and Semenov MA (2000) Modelling CO2 effects on wheat with varying nitrogen supplies. Agriculture, Ecosystems and Environment 82: 27-37. doi:10.1016/s0167-8809(00)00214-0.

Jarvis A, Lane A and Hijmans RJ (2008) The effect of climate change on crop wild relatives. Agriculture, Ecosystems and Environment 126: 13-23. doi:DOI: 10.1016/j.agee.2008.01.013.

Jarvis A, Lau C, Cook S, Wollenberg E, Hansen J, Bonilla O and Challinor A (2011) An Integrated Adaptation and Mitigation Framework for Developing Agricultural Research: Synergies and Trade-offs. Experimental Agriculture 47: 185-203. doi:doi:10.1017/S0014479711000123.

Jarvis A, Ramirez J, Anderson B, Leibing C and Aggarwal P (2010) Scenarios of Climate Change Within the Context of Agriculture. CAB International.

Jones JW, Hoogenboom G, Porter CH, Boote KJ, Batchelor WD, Hunt LA, Wilkens PW, Singh U, Gijsman AJ and Ritchie JT (2003) The DSSAT cropping system model. European Journal of Agronomy 18: 235-265. doi:Doi: 10.1016/s1161-0301(02)00107-7.

Jones PG and Thornton PK (2003) The potential impacts of climate change on maize production in Africa and Latin America in 2055. Global Environmental Change 13: 51-59. doi:Doi: 10.1016/s0959-3780(02)00090-0.

Kamukondiwa W (1996) Alternative food crops to adapt to potential climatic change in southern Africa. Climate Research 06: 153-155. doi:10.3354/cr0006153.

Leakey ADB, Ainsworth EA, Bernacchi CJ, Rogers A, Long SP and Ort DR (2009) Elevated CO2 effects on plant carbon, nitrogen, and water relations: six important lessons from FACE. Journal of Experimental Botany 60: 2859-2876. doi:10.1093/jxb/erp096.

Liu J, Fritz S, van Wesenbeeck CFA, Fuchs M, You L, Obersteiner M and Yang H (2008) A spatially explicit assessment of current and future hotspots of hunger in Sub-Saharan Africa in the context of global change. Global and Planetary Change 64: 222-235. doi:DOI: 10.1016/j.gloplacha.2008.09.007.

Lobell DB, Burke MB, Tebaldi C, Mastrandrea MD, Falcon WP and Naylor RL (2008) Prioritizing Climate Change Adaptation Needs for Food Security in 2030. Science 319: 607-610. doi:10.1126/science.1152339.

Majda AJ and Gershgorin B (2010) Quantifying uncertainty in climate change science through empirical information theory. Proceedings of the National Academy of Sciences 107: 14958-14963. doi:10.1073/pnas.1007009107.

Matsueda M and Palmer TN (2011) Accuracy of climate change predictions using high resolution simulations as surrogates of truth. Geophys. Res. Lett. 38: L05803. doi:10.1029/2010gl046618.

Mbanzibwa DR, Tian YP, Tugume AK, Mukasa SB, Tairo F, Kyamanywa S, Kullaya A and Valkonen JPT (2011) Simultaneous virus-specific detection of the two cassava brown streak-associated viruses by RT-PCR reveals wide distribution in East Africa, mixed infections, and infections in Manihot glaziovii. Journal of Virological Methods 171: 394-400. doi:10.1016/j.jviromet.2010.09.024.

Monger W, Alicai T, Ndunguru J, Kinyua Z, Potts M, Reeder R, Miano D, Adams I, Boonham N, Glover R and Smith J (2010) The complete genome sequence of the Tanzanian strain of andlt;iandgt;Cassava brown streak virusandlt;/iandgt; and comparison with the Ugandan strain sequence. Archives of Virology 155: 429-433. doi:10.1007/s00705-009-0581-8.

Moss RH, Edmonds JA, Hibbard KA, Manning MR, Rose SK, van Vuuren DP, Carter TR, Emori S, Kainuma M, Kram T, Meehl GA, Mitchell JFB, Nakicenovic N, Riahi K, Smith SJ, Stouffer RJ, Thomson AM, Weyant JP and Wilbanks TJ (2010) The next generation of scenarios for climate change research and assessment. Nature 463: 747-756. doi:http://www.nature.com/nature/journal/v463/n7282/suppinfo/nature08823_S1.html.

Mulligan M, Fisher M, Sharma B, Xu ZX, Ringler C, Mahé G, Jarvis A, Ramírez J, Clanet J-C, Ogilvie A and Ahmad M-u-D (2011) The nature and impact of climate change in the Challenge Program on Water and Food (CPWF) basins. Water International 36: 96-124. doi:10.1080/02508060.2011.543408.

Neelin JD, Münnich M, Su H, Meyerson JE and Holloway CE (2006) Tropical drying trends in global warming models and observations. Proceedings of the National Academy of Sciences 103: 6110-6115. doi:10.1073/pnas.0601798103.

Neuenschwander P (2001) Biological Control of the Cassava Mealybug in Africa: A Review. Biological Control 21: 214-229. doi:10.1006/bcon.2001.0937.

Nicholson SE, Some B and Kone B (2000) An Analysis of Recent Rainfall Conditions in West Africa, Including the Rainy Seasons of the 1997 El Niño and the 1998 La Niña Years. Journal of Climate 13: 2628-2640. doi:10.1175/1520-0442(2000)013<2628:aaorrc>2.0.co;2.

Olsen KM and Schaal BA (1999) Evidence on the origin of cassava: Phylogeography of Manihot esculenta. Proceedings of the National Academy of Sciences of the United States of America 96: 5586-5591.

Patil BL and Fauquet CM (2009) Cassava mosaic geminiviruses: actual knowledge and perspectives. Molecular Plant Pathology 10: 685-701. doi:10.1111/j.1364-3703.2009.00559.x.

PCMDI (2007) IPCC Model Output. Available at: http://www.pcmdi.llnl.gov/ipcc/about_ipcc.php.

Peterson TC and Vose RS (1997) An Overview of the Global Historical Climatology Network Temperature Database. Bulletin of the American Meteorological Society 78: 2837-2849. doi:doi:10.1175/1520-0477(1997)078<2837:AOOTGH>2.0.CO;2.

Phillips SJ, Anderson RP and Schapire RE (2006) Maximum entropy modeling of species geographic distributions. Ecological Modelling 190: 231-259. doi:DOI: 10.1016/j.ecolmodel.2005.03.026.

Pierce DW, Barnett TP, Santer BD and Gleckler PJ (2009) Selecting global climate models for regional climate change studies. Proceedings of the National Academy of Sciences 106: 8441-8446. doi:10.1073/pnas.0900094106.

Prasad PVV, Boote KJ, Allen LH and Thomas JMG (2002) Effects of elevated temperature and carbon dioxide on seed-set and yield of kidney bean (Phaseolus vulgaris L.). Global Change Biology 8: 710-721. doi:10.1046/j.1365-2486.2002.00508.x.

Quiggin J (2008) Uncertainty and Climate Change Policy. Economic Analysis and Policy 38: 203-210.

R Development Core Team (2011) R: A language and environment for statistical computing. R Foundation for Statistical Computing., Vienna, Austria.

Ramirez-Villegas J, Jarvis A and Läderach P (2011) Empirical approaches for assessing impacts of climate change on agriculture: The EcoCrop model and a case study with grain sorghum. Agricultural and Forest Meteorology. *In press.* doi:10.1016/j.agrformet.2011.09.005.

Ramirez J and Bueno-Cabrera A (2009) Working with climate data and niche modeling I. Creation of bioclimatic variables: International Center for Tropical Agriculture (CIAT), Cali, Colombia.

Ramirez J and Jarvis A (2010) Downscaling Global Circulation Model Outputs: The Delta Method. Decision and Policy Analysis Working Paper No. 1: International Center for Tropical Agriculture (CIAT), Cali, Colombia.

Ramirez J, Jarvis A, Van den Bergh I, Staver C and Turner D (2011) Chapter 20: Changing Climates: Effects on Growing Conditions for Banana and Plantain (Musa spp.) and Possible Responses. Wiley and Sons.

Richardson CW (1981) Stochastic simulation of daily precipitation, temperature, and solar radiation. Water Resour. Res. 17: 182-190. doi:10.1029/WR017i001p00182.

Roudier P, Sultan B, Quirion P and Berg A (2011) The impact of future climate change on West African crop yields: What does the recent literature say? Global Environmental Change 21: 1073-1083. doi:10.1016/j.gloenvcha.2011.04.007.

Schafleitner R, Ramirez J, Jarvis A, Evers D, Gutierrez R and Scurrah M (2011) Chapter 11: Adaptation of the Potato Crop to Changing Climates. Wiley and Sons.

Schlenker W and Lobell DB (2010) Robust negative impacts of climate change on African agriculture. Environmental Research Letters 5: 014010.

Schroth G, Laderach P, Dempewolf J, Philpott S, Haggar J, Eakin H, Castillejos T, Garcia Moreno J, Soto Pinto L, Hernandez R, Eitzinger A and Ramirez-Villegas J (2009) Towards a climate change adaptation strategy for coffee communities and ecosystems in the Sierra Madre de Chiapas, Mexico. Mitigation and Adaptation Strategies for Global Change 14: 605-625. doi:citeulike-article-id:5394445.

Tao F, Yokozawa M and Zhang Z (2009) Modelling the impacts of weather and climate variability on crop productivity over a large area: A new process-based model development, optimization, and uncertainties analysis. Agricultural and Forest Meteorology 149: 831-850. doi:10.1016/j.agrformet.2008.11.004.

Thornton PK, Jones PG, Ericksen PJ and Challinor AJ (2011) Agriculture and food systems in sub-Saharan Africa in a 4°C+ world. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences 369: 117-136. doi:10.1098/rsta.2010.0246.

Thresh JM, Otim-Nape GW, Thankappan M and Muniyappa V (1998) The mosaic diseases of cassava in Africa and India caused by whitefly-borne geminiviruses. Review of Plant Pathology 77: 935-945.

Trujillo HE, Arias B, Guerrero JM, Hernandez P, Bellotti A and Peña JE (2004) Survey of Parasitoids of Whiteflies (Homoptera: Aleyrodidae) in Cassava Growing Regions of Colombia and Ecuador. Florida Entomologist 87: 268-273. doi:10.1653/0015-4040(2004)087[0268:sopowh]2.0.co;2.

Wilby RL, Troni J, Biot Y, Tedd L, Hewitson BC, Smith DM and Sutton RT (2009) A review of climate risk information for adaptation and development planning. International Journal of Climatology 29: 1193-1215. doi:10.1002/joc.1839.

Winter S, Koerbler M, Stein B, Pietruszka A, Paape M and Butgereitt A (2010) Analysis of cassava brown streak viruses reveals the presence of distinct virus species causing cassava brown streak disease in East Africa. Journal of General Virology 91: 1365-1372. doi:10.1099/vir.0.014688-0.

Yaninek JS and Herren HR (1988) Introduction and spread of the cassava green mite, Mononychellus tanajoa (Bondar) (Acari: Tetranychidae), an exotic pest in Africa and the search for appropriate control methods: a review. Bulletin of Entomological Research 78: 1-13. doi:doi:10.1017/S0007485300016023.

You L, Wood S and Wood-Sichra U (2009) Generating plausible crop distribution maps for Sub-Saharan Africa using a spatially disaggregated data fusion and optimization approach. Agricultural Systems 99: 126-140. doi:DOI: 10.1016/j.agsy.2008.11.003.

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SUPPORTING INFORMATION

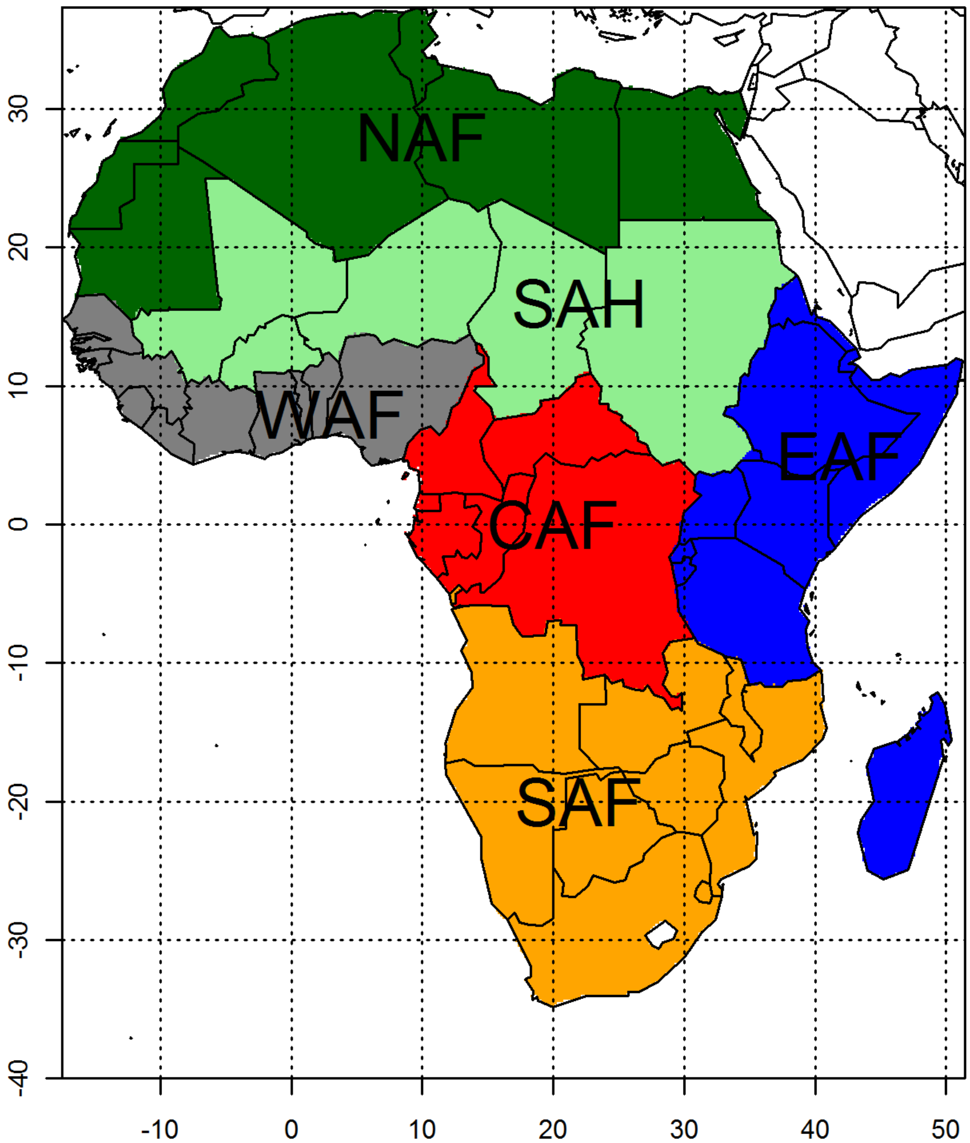

Figure S1 Zone typology in the African continent as used in the study, designed to match with the study of Lobell et al. (Lobell et al., 2008)