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Potential adaptive strategies for 29 sub-Saharan crops under future climate change

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Climate change is expected to severely impact cultivated plants and consequently human livelihoods[1–3], especially in sub-Saharan Africa (SSA)[4–6]. Increasing agricultural plant diversity (agrobiodiversity) could overcome this global challenge[7–9] given more information on the climatic tolerance of crops and their wild relatives. Using >200,000 worldwide occurrence records for 29 major crops and 778 of their wild relative species, we assess, for each crop, how future climatic conditions are expected to change in SSA and whether populations of the same crop from other continents, wild relatives around the world or other crops from SSA are better adapted to expected future climatic conditions in the region. We show that climate conditions not currently experienced by the 29 crops in SSA are predicted to become widespread, increasing production insecurity, especially for yams. However, crops such as potato, squash and finger millet may be maintained by using wild relatives or non-African crop populations with climatic niches more suited to future conditions. Crop insecurity increases over time and with rising GHG emissions, but the potential for using agrobiodiversity for resilience is less altered. Climate change will therefore affect sub-Saharan agriculture but agrobiodiversity can provide resilient solutions in the short and medium term.

Global climate has changed rapidly over recent decades, and temperature and precipitation regimes are predicted to shift significantly in the near future[10]. Future impacts on both biodiversity and human livelihoods are significant and primarily negative[2,4,11]. By affecting plant productivity, and thus industrial and food crop yield, climate change is expected to impact global human economy and subsistence[1,2]. Its tropical location, socioeconomic, demographic, policy and farming characteristics place sub-Saharan Africa (SSA) at major risk[5,6]. Assessing which sub-Saharan crops, regions and populations will be most affected, as well as potential future adaptations, is therefore essential.

Agrobiodiversity and breeding programmes are an important adaptive strategy for agriculture in a changing world[8,12]. Currently cultivated crops may exhibit reduced genetic variation compared to that found in wild relative populations, which may limit their resilience and adaptation to future environmental conditions[13]. Crop improvement through selection for traits from other landraces or wild relatives could confer resilience to changing climates and increase crop survival, growth and yield. Therefore, preserving and increasing breeding germplasm diversity by identifying and targeting crop diversity and wild relatives is an important first step[14,15]. Here, we quantify the expected shifts in climatic conditions by 2050 and 2070 for 29 major crops across SSA. We then assess whether non-African crop populations, wild relatives around the world and/or other sub-Saharan crops with different climate tolerances can offer alternative, more resilient varieties to the problem of climate change.

We collected occurrence records for 29 crop species widely cultivated in SSA and 778 of their wild relatives worldwide (Supplementary Tables 1 and 2). The selected crop species include cereals, starch staples, vegetables, edible fruits and commodity crops, most of which are key to subsistence and economy as they provided >2,040 kcal per capita per day and a total gross production of >US$108 billion across Africa for 2013 and 2016, respectively[16]. Using principal component analyses and minimum convex polygons with outlier detection (see Methods), we related each crop's occurrences to multiple climatic (mean, seasonal and extreme temperature and precipitation) and topographic variables essential to plant development to estimate their current climatic niches (defined as a two-dimensional climate space) in SSA. We then identified future climates expected at the current locations of each crop by 2050 and 2070 according to 14 general circulation models (GCMs) and two GHG emission scenarios: representative concentration pathways (RCPs) 4.5 and 8.5. RCP 4.5 represents a mid-to-low end emission scenario that considers a peak in GHG emissions around 2040 and a decline afterwards, better matching the targets set by the Paris Agreement of the United Nations Framework Convention on Climate Change (UNFCCC)[17], whereas RCP 8.5 represents an extreme scenario for which emissions are expected to increase throughout the twenty-first century. Finally, we estimated the potential security of each crop as the proportion of future climatic space currently experienced by the crop (Fig. 1). All crop occurrences were assumed to represent rain-fed and non-fertilized populations given the low proportion of irrigated/fertilized land across SSA, but possible expansions of crop niches due to these or other human management factors (for example, weed control) cannot be fully discarded[18,19].

The potential of three strategies was then assessed. First, as climatic niche shifts are common in cultivated plants across continents[20], we evaluated whether populations from other world biogeographic regions exist in the expected new future climatic conditions for each crop. Second, because wild relatives occur in many different natural environments and may exhibit traits adapted to specific climatic conditions[13–15], we assessed whether wild relatives have already shown adaptation to the expected new future climatic conditions of each crop. Third, a crop that cannot be grown under new climatic conditions could be replaced with alternative crops that fulfil similar or different nutritional and/or economic needs[21].

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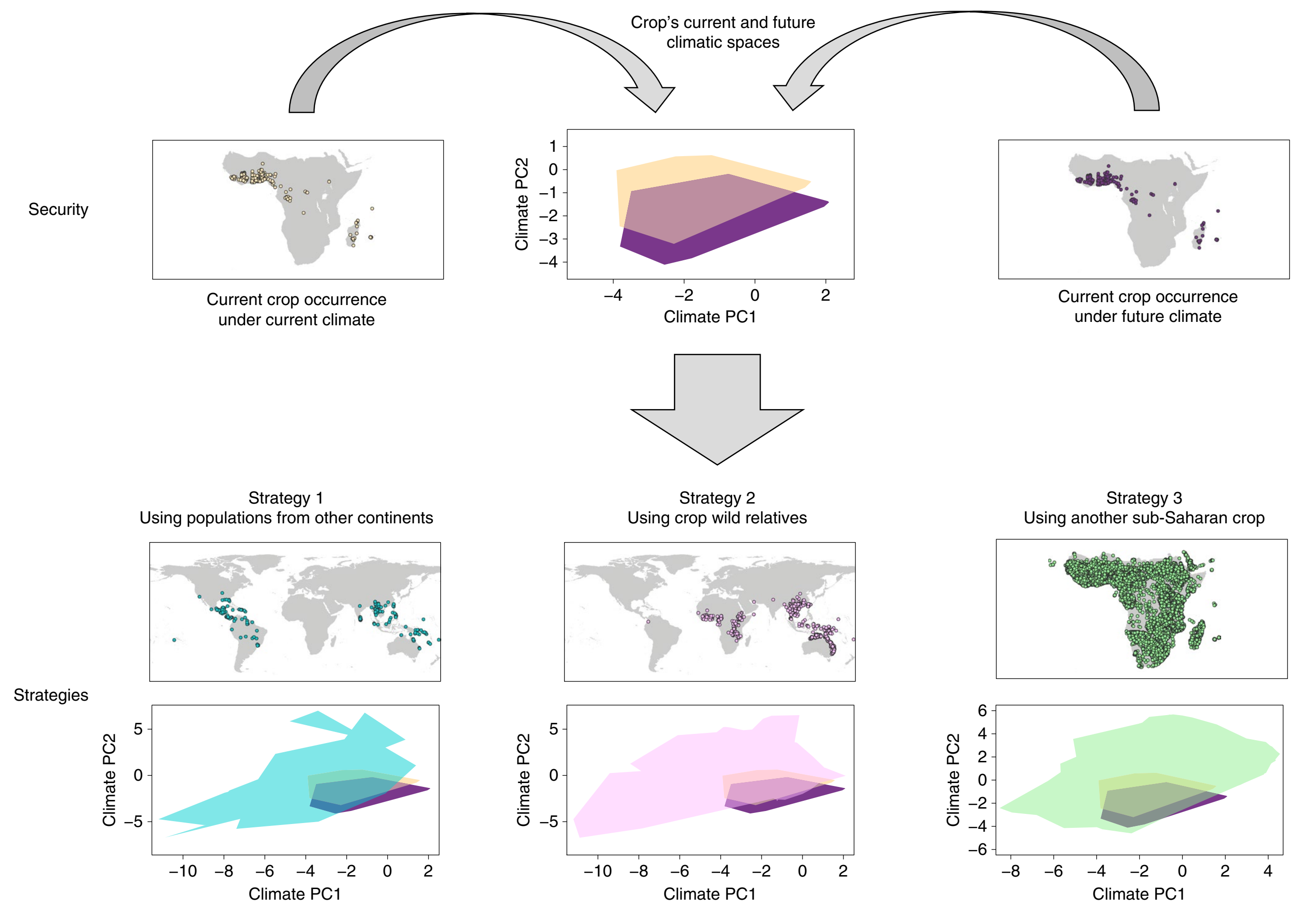

Fig. 1 | Analytical framework. Top: An index of crop security was measured for each of the 29 crop species as the overlap between their climatic niches, estimated from the current distribution in the Afrotropics (beige) and the expected future climatic conditions in these areas (purple). Bottom: Indices representing three adaptive strategies were then measured for each crop as the overlap between the new climate expected for the crop in the future (purple) and the estimated climatic niches of the same crop in other regions of the world (blue), its wild relatives across all continents (pink) and the other 28 crops in the Afrotropics (green). The winged yam (*Dioscorea alata*) was taken as an example here.

Therefore, we assessed whether each crop's expected new future climatic conditions were within the current tolerance range of each of the other 28 sub-Saharan crops (Fig. 1). Alternative strategies may be considered to adapt to future climate change[9,21], such as genetic engineering[22], but we assessed only those that represent significant continent-wide solutions related to agrobiodiversity, and for which there is credible data consistency and availability.

As climate is expected to change substantially in SSA, by 2050 and 2070, respectively, ~12% and ~26% of the future climate space is expected to be novel where the 29 crop species currently grow (Figs. 2 and 3, Supplementary Table 1 and Supplementary Fig. 1). These percentages vary according to the GCM or niche quantification measure considered, but increase significantly in 2070 from projected low to high GHG emission scenario (Fig. 3 and Supplementary Figs. 1–4). For a few crops, the emergence of new climates is expected to be especially strong, which is in agreement with previous findings[23]. For example, the future of the Guinea yam is particularly uncertain given that ~56% of its future climate is expected to be new by 2070. This is due to its relatively small distribution, mainly in West Africa, where current conditions are some of the warmest and wettest found in SSA, and even warmer and wetter conditions are forecast by the end of the century[24] (Supplementary Fig. 5).

Several regions may benefit from all three adaptive strategies (for example, those cultivating finger millet, potato, squash and Arabica coffee; Fig. 2, Supplementary Table 1 and Supplementary Fig. 1). Other regions may benefit from using populations from other continents (for example, those cultivating pea and taro) or using wild relatives in breeding programmes to ensure resilience genes that enable greater climatic tolerance once (re-)established in the crop (for example, sugarcane). However, crops such as Guinea yam may experience such novel climatic conditions in the future that, in the worst-case scenario, they may need replacement by more suitable crops. Compared to crop insecurity, the potential for the three adaptive strategies may not decrease so drastically from 2050 to 2070 nor from a low to high end GHG emission scenario, but it may vary substantially among crop species (Fig. 3). Although crop-specific, this result highlights a relative persistence of the potential for adaptation over increasing climate change intensity despite the increasing novelty of conditions experienced by the crops.

Unsurprisingly, most non-sub-Saharan populations that may fare better under future climate conditions occur in other tropical areas (Fig. 4a; Kruskal–Wallis test: $X^2 = 73.6$, degrees of freedom (d.f.) $= 5$, $P < 0.001$; Supplementary Table 3 and Supplementary Fig. 6). More interestingly, potentially resilient cultivars are found both in the Neotropics and Indomalay regions (for example, common bean), or mainly from one or the other (for example, Neotropics for potato and squash, Indomalay for pea and finger millet). These results reflect additional potential for certain crops

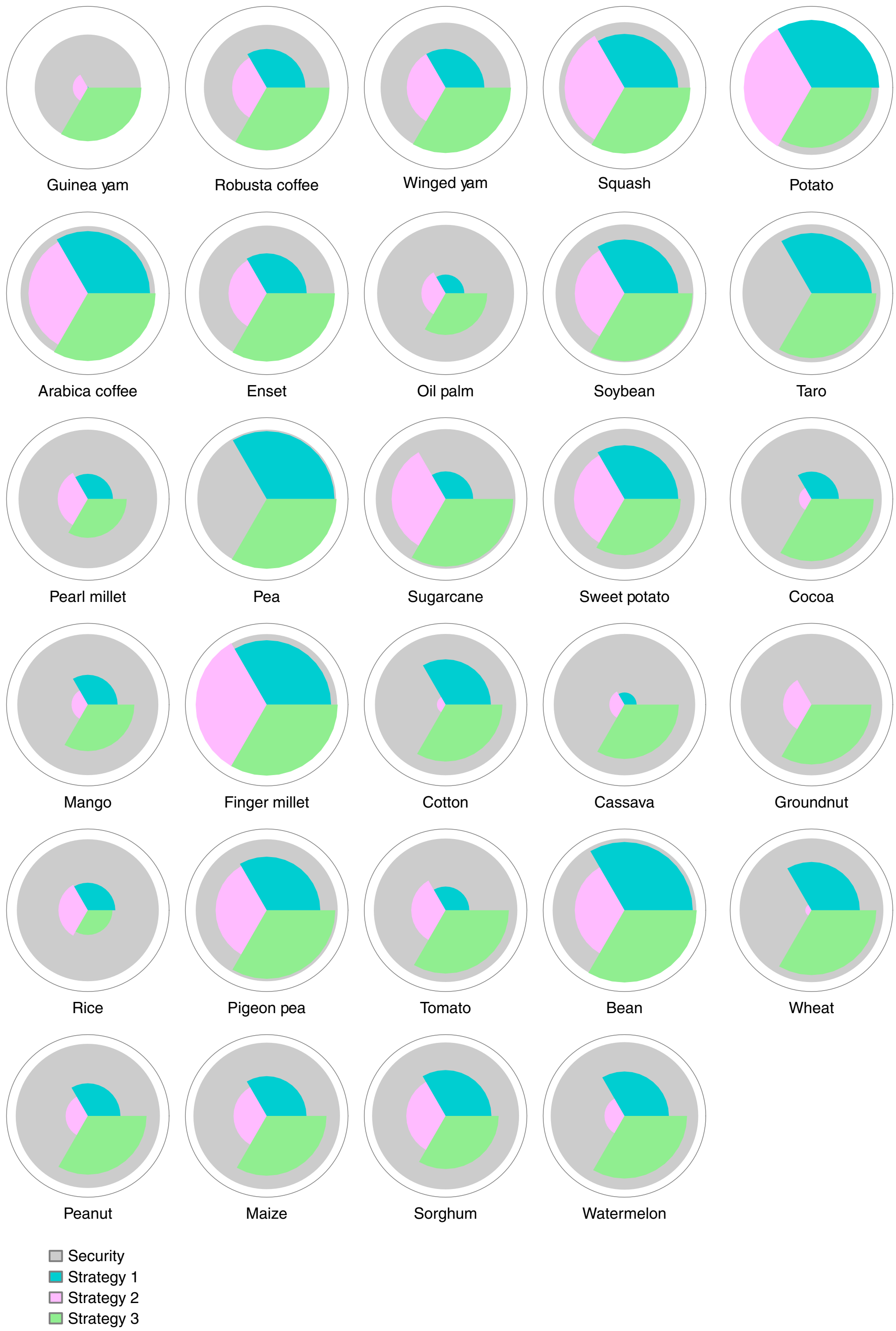

Fig. 2 | Potential security and adaptive strategies for 29 sub-Saharan crops under future climate change by 2070. The 29 crops are ordered from high (upper left) to low risk (lower right) of being impacted by climate change. Percentages of overlap between the crops' current climatic niches and projected future climatic conditions in the areas of current crop cultivation are represented by the proportion of the circle covered by the grey disk. The potential success of the three strategies is represented by the sizes of the pie slices. Percentages of overlap with the new climate expected in the future are represented by the slices' areas within the grey disk, where 100% overlap for one strategy results in a third of the grey disk being covered. This figure provides median overlap values across all GCMs, RCPs and outlier selection thresholds for the year 2070. Results for 2050 and each GCM, RCP and outlier selection are provided in the Supplementary Information.

to survive under climate change in SSA, the possibility for cultivation of populations from other regions or the potential for initiating intercontinental breeding programmes between sub-Saharan and other regions' crop diversity[24]. This last approach is particularly promising, as illustrated by the recent release of new potato varieties in Kenya from the International Potato Center, Lima, Peru (CIP),

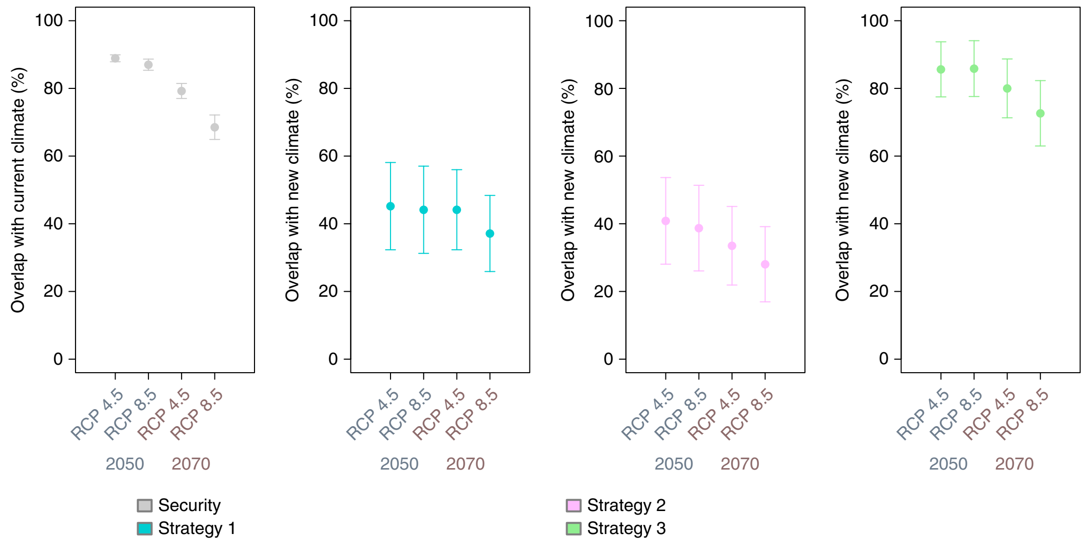

Fig. 3 | Potential security and adaptive strategies for 29 sub-Saharan crops under different scenarios of future climate change. Mean and 95% confidence intervals are given for each overlap value across all crops, GCMs and outlier selection, and for each time period (2050 and 2070) and RCP scenario. Results for each crop, GCM and outlier selection are provided in the Supplementary Information.

which maintain significant yield under lower precipitation and higher temperatures[25]. However, as farmers in other continents tend to use significantly more irrigation and fertilization than Africa[18,19], the pattern found in our study may be an overestimate and reflect instead the potential for persistence of the crop with improved agricultural practices.

The potential for using wild relatives to improve the 29 crops does not appear to be associated with the degree of genetic relatedness between crops and their wild relatives (Fig. 4b; Kruskal–Wallis test: $X^2=5.3$, d.f. $=3$, $P=0.15$; Supplementary Tables 2 and 4 and Supplementary Fig. 6). For a given crop, genetically closer wild relatives (belonging to the primary gene pool; see Methods) are not necessarily more adapted to expected future climates than more distant relatives, and vice versa. In some cases, such as with finger millet, breeding with a very closely related species (such as *Eleusine indica*), which may increase the chances of successful hybridization, may result in future climate adaptation. Conversely, other crops may benefit from potentially challenging introgression from more distant wild relatives (for example, soybean and its wild relative *Glycine tomentella*). Several wild species identified in this study to be of interest have already been considered for breeding programmes to provide, for example, drought and heat resistance in potato (*Solanum chacoense*), drought or waterlogging tolerance in sugarcane (*Saccharum arundinaceum*), pest resistance in coffee (*Coffea liberica*) or improved yield in sorghum (*Sorghum propinquum*), which attests to the potential of our approach to contribute to the selection of wild relatives for crop improvement (see https://www.cwrdiversity.org/checklist/[15] for a detailed list of references about previous breeding efforts using specific wild relatives). Moreover, this potential may be underestimated, as many wild relatives remain to be discovered and catalogued[14,15]. Less positively, breeding programmes involving wild relatives, especially from secondary and tertiary gene pools, often require large investments of research, money and time to achieve both technical success (for example, providing increased climatic resilience without losing nutritional value) and adoption by farmers and consumers[26].

Our results show that most crops have the climatic potential to be replaced in the future, mainly by other crops that are currently found in a large range of climatic environments and/or that are specific to particularly warm areas (Fig. 4c, Supplementary Table 5 and Supplementary Fig. 6). This is the case for cassava, peanut and sorghum, as also highlighted in a previous study[21]. However, several other potential replacement crops require additional resources to be cultivated (for example, paddy rice requires irrigation) or are industrial crops (for example, cotton and oil palm), which may not necessarily guarantee food security. Conversely, crops such as the common bean, yams or the 'false banana' enset have been identified as poor candidates to replace other crops[21]. This result might not only reflect the physiological capacity of crops but also regional cultural preferences. For example, enset, which requires substantial ethnobotanical knowledge for cultivation and processing, is only cultivated in Ethiopia, although undomesticated enset occurs sparsely in other African countries. However, it is considered a potential crop for future food security due to its tolerance to drought and its high productivity[27]. Major and orphan crops other than the 29 studied here could also be considered, which might eventually reinforce a replacement strategy.

Although this study represents a broad exploration of the options for providing resilient sub-Saharan crops under climate change at unprecedented geographic and taxonomic scales and relies on a large amount of information, several limitations are to be noted. The documentation of the global distribution of crops and their wild relatives is still incomplete[14]: collecting more and finer occurrence data, especially in regions with current climatic conditions similar to those projected in the future for a given area of interest, will greatly help in refining these results. Given that other factors act in synergy with the average climate for the crops and their wild relatives to grow and/or produce[28,29], the effects of extreme climatic events, soil quality, plant genetics or functional specificities, crop pests, human agricultural and cultural practices, or atmospheric CO_2 levels are to be considered in future work. Finally, previous studies on a few major crops predicted losses in production and area of up to 15% by 2050 and 30% by the end of the twenty-first century[3,21], which match our estimates of crop insecurity relatively well. Nevertheless, the relationship between crop occurrence, environmental suitability and yield remains poorly known. In this context, combining correlative and process-based approaches will be key to improve predictions of the impact of climate change on sub-Saharan agriculture and human livelihoods[3].

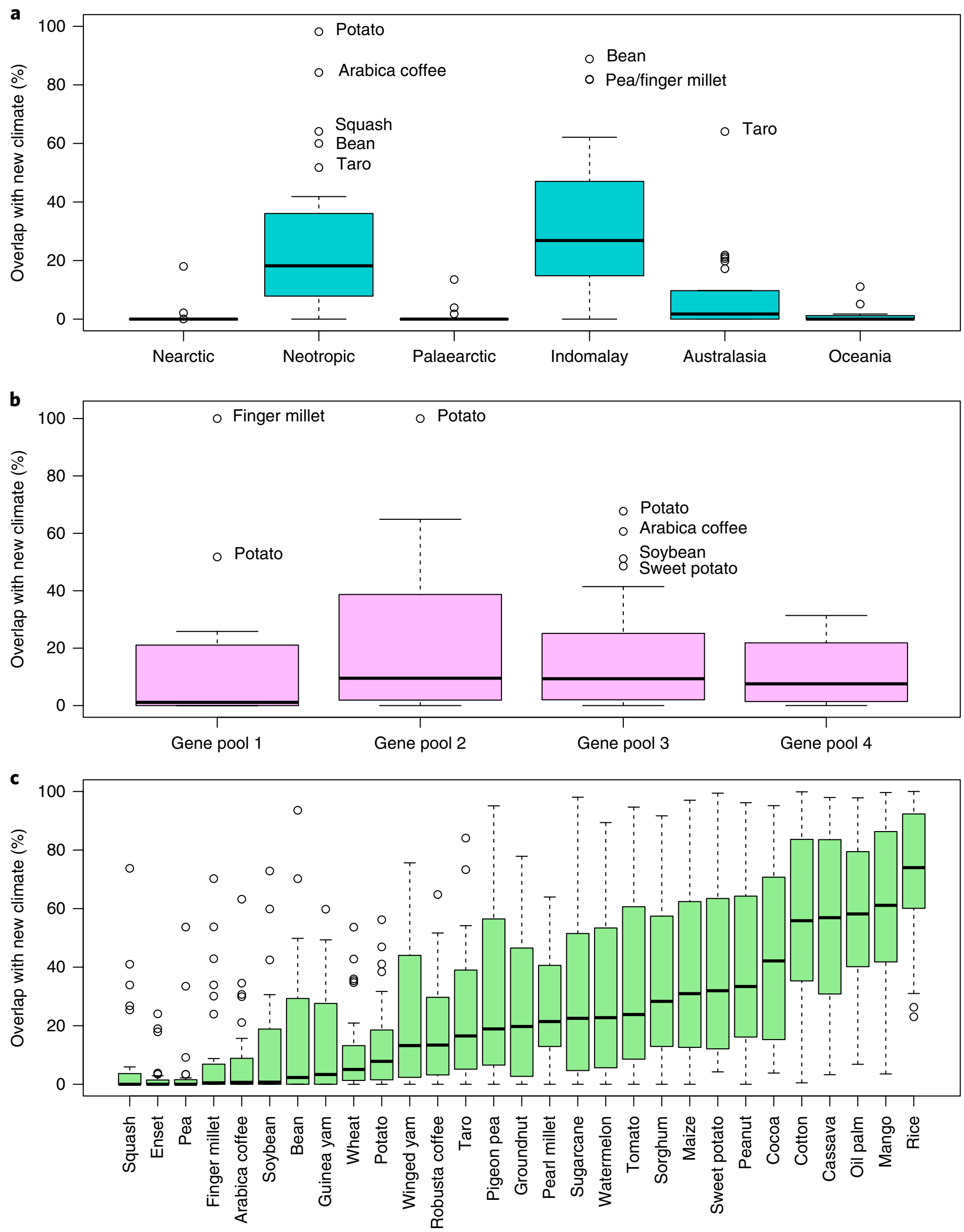

Fig. 4 | Details of the three potential adaptive strategies under future climate change by 2070. a–c, Regions of origin of the non-African populations (**a**), gene pools of the crop wild relatives (**b**) and identities of the sub-Saharan crops providing more solutions (**c**), with upper and lower extremes, quartiles, medians and outliers of the percentages of overlap between the new climate expected in the future in the areas currently growing each of the 29 crops in the Afrotropics and the current climatic niches of the same crops from different biogeographical realms (**a**), their wild relatives from different gene pools (**b**) and each of the 29 sub-Saharan crops (**c**). Results for 2050 and for each crop are provided in the Supplementary Information.

Different adaptive strategies may be available for SSA to face the detrimental effects of future climate change in the short and medium term. Although crop substitution may be implemented more rapidly than crop improvement, social factors such as local investments in agricultural research and development, cultural preferences and time for adoption and diffusion of new cultivars must also be considered[26]. Overall, our study shows that agrobiodiversity, fusing the rich world diversity in crops and wild relatives, can represent a major solution through a global benefit sharing system[30]. Preserving, studying, exchanging and using this diversity responsibly and sustainably is therefore essential in times of serious economic, demographic and environmental change in SSA.

Online content

Any methods, additional references, Nature Research reporting summaries, source data, statements of code and data availability and associated accession codes are available at https://doi.org/10.1038/s41558-019-0585-7.

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Author contributions

S.P., T.R.E., M.M.-F. and K.J.W. designed the study with help from all co-authors. S.P., N.K. and J.S.B. collected data. S.P. analysed the data with help from I.O. S.P. wrote the manuscript, with substantial help from all co-authors.

Competing interests

The authors declare no competing interests.

Additional information

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Methods

Study species. We studied 29 different crop species and 778 of their wild relatives (Supplementary Tables 1 and 2). The 29 crop species were chosen if (1) they were known to be cultivated relatively widely in SSA according to both the FAO[16] and experts from Royal Botanic Gardens Kew, UK and the Council for Scientific and Industrial Research (CSIR), South Africa, (2) reliable and numerous occurrence data were available across their known distribution in SSA and (3) their wild relatives could be identified. Most crops are food crops, but some are industrial (for example, cotton). Out of the 29 crops, 27 genera are represented (given the presence of two yam species (*Dioscorea rotundata–cayenensis* complex and *D. alata*) and two coffee species (*Coffea arabica* and *C. canephora*)). The crops comprise different life forms (trees, shrubs, herbs and vines) and longevities (annuals and perennials). Because of the relatively poor taxonomic and geographic quality of infra-specific/hybrid data, we decided to work at a species level for both crops and wild relatives. The identity of 967 wild relative species of the 29 crops was therefore retrieved from the project 'Adapting agriculture to climate change: collecting, protecting and preparing crop wild relatives' (https://www.cwrdiversity.org[15]) in November 2016. As part of this project, each wild relative was assigned a degree of relatedness to its associated crop following a four-gene-pool classification[31,32], with the species from the primary gene pool considered to be more closely related to the crop and therefore easier to breed with it than the species from the fourth. We used this classification because (1) it is based directly on plant crossing ability and past utility and (2) complete phylogenies are not available for many of our species of interest. We discarded 189 out of the 967 species as these did not have the minimum three occurrences necessary for conducting climatic niche analyses (see 'Occurrence data'). Thirty-nine genera were represented within the final list of 778 wild relatives. Finally, it is important to note that the 778 species are considered wild relatives in a broad sense, given that some of them may have also been partly domesticated.

Occurrence data. Worldwide occurrence records for the 29 crops and 778 wild relatives were collected from several sources: the crop wild relative global occurrence database compiled by the project 'Adapting agriculture to climate change: collecting, protecting and preparing crop wild relatives' (https://www.cwrdiversity.org), the Global Biodiversity Information Facility database (GBIF, https://www.gbif.org), the Genesys database from the global portal to information about Plant Genetic Resources for Food and Agriculture (PGRFA, https://www.genesys-pgr.org), the Rainbio database, which covers all continental SSA[33], agricultural surveys conducted in more than 9,500 households across 11 African countries[34] and in more than 1,000 households across Ghana, Malawi and Swaziland from collaborators of the FICESSA project (https://supportoffice.jp/ficessa/). We used primary occurrence data rather than modelled distributions or downscaled census data, as those are not consistently available for all crops and wild relatives and, when available, they are of highly disparate quality and resolution and tend to largely overestimate species distributions, especially in SSA. GBIF occurrence data were extracted using the dismo package[35] in R[36]. The online version of the Rainbio database provides access to occurrences of non-cultivated plant species only, but data for cultivated ones were also obtained directly from the authors. Crop occurrence data from Genesys that were not collected in the field (that is, from markets and stores) were discarded. For some agricultural survey records, household geographic coordinates were not available and names of administrative areas were given instead. For those occurring in small areas fitting in 10 arc minutes (~20 km) grid cells, we kept the coordinates of the centres of the cells, while we discarded other imprecise or ambiguous records. We cleaned the entire dataset further by discarding species' occurrence records falling in the same 10 arc minutes grid cells, non-contemporary data (for example, fossils and records older than 1950), coordinates equal to zero or any other integer value and points falling in the sea. From an original dataset of >1,000,000 points, we retrieved a total of 202,908 unique occurrence records for the 29 crops and their 778 wild relatives worldwide. Additionally, we categorized the region of occurrence of each record by using a biogeographical realm map provided by http://ecoregions2017.appspot.com[37]. We used a biogeographical realm map rather than a continental one to consider SSA as one unique region (that is, Afrotropic) and to have a more ecologically meaningful classification.

Climate data. Given the global extent of our study, we used environmental information that was available and comparable at such a large geographic scale. The CHELSA database[38] provides temperature and precipitation data downscaled at high resolution for the years 1979–2013 (hereafter considered as the 'current' climate), as well as future climate projections obtained by several downscaled GCMs used in the Fifth Assessment Report of the IPCC[10]. CHELSA has been shown to predict temperature patterns similarly to other climate data sources and to perform better for precipitation, providing better overall estimates of species climatic niches and distributions, especially in areas with poor weather stations coverage, such as SSA and other tropical countries[38]. The present climatic data from CHELSA also matched best the temporal resolution of our species occurrence information (Supplementary Fig. 7). We collected eight different bioclimatic variables from the CHELSA database at a 30 arc seconds (~1 km) resolution: annual mean temperature (BIO1), temperature seasonality (BIO4), maximum temperature of the warmest month (BIO5), minimum temperature of the coldest month (BIO6), annual mean precipitation (BIO12), precipitation of the wettest (BIO13) and driest (BIO14) months and precipitation seasonality (BIO15). These eight variables were selected to capture mean, seasonal and extreme (potentially limiting) temperature and precipitation conditions that can be essential to the survival and growth of domesticated and wild plant species. Despite each plant species (and each plant function or vital rate) being affected by climate in a different way[39], considering different climatic variables for each species was discarded because (1) information about species climatic preferences or tolerance is not available for so many species and (2) our analyses aim at comparing species climatic ranges, so the latter must be analysed in a climate space built upon the same variables. Our variable selection covers the full spectrum of the 19 inter-related bioclimatic variables available in CHELSA (Supplementary Fig. 8). This selection therefore limits the incorporation of repetitive information and enables clear interpretations. Indeed, although some of the eight selected variables may still be partly correlated, multi-collinearity is not an issue in the multivariate analyses conducted in our study. Climate layers were upscaled to 10 arc minutes resolution (~20 km) using the resample function from the raster package[40] in R. We worked at such a resolution for several reasons: (1) to avoid incorrect assignment of climatic variables to the occurrence records for which precision is not necessarily communicated by data sources[41,42], (2) future climatic data are downscaled from coarse GCMs and therefore can only assess large-scale patterns[43] and (3) climate is expected to be the main driver at large scales, whereas other factors might become more important with lower grain size[44]. Our study therefore focuses on macroclimatic, rather than microclimatic conditions. For future climate conditions, we used data for the 2050 and 2070 time periods (averages for 2041–2060 and 2061–2080, respectively) generated by 14 GCMs and following two GHG emissions scenarios. Considering different climate models' outputs and socio-economic scenarios has been shown to be essential for agricultural or biodiversity risk assessments[45,46]. The 14 GCMs were ACCESS 1–0 (AC), BCC-CSM1-1 (BC), CCSM4 (CC), CNRM-CM5 (CN), HadGEM2-AO (HD), HadGEM2-CC (HG), INMCM4 (IN), IPSL-CM5A-LR (IP), MIROC-ESM-CHEM (MI), MIROC-ESM (MR), MIROC5 (MC), MPI-ESM-LR (MP), MRI-CGCM3 (MG) and NorESM1-M (NO). We selected these 14 models based on data availability and in order to cover most of the inter-model variability[47]. The two GHG scenarios were RCPs 4.5 and 8.5. RCP 4.5 represents a mid to low end emission scenario that matches best the targets set by the Paris Agreement of the UNFCCC[17]. Finally, because large-scale climatic averages might not necessarily represent differences in topography well, we also included a slope variable to our analyses. Land slope was computed by applying the slope function from the Spatial Analyst geoprocessing toolbox from the Arc/Info GIS ESRI suite of products to a digital elevation model (DEM) provided by the Global Multi-resolution Terrain Elevation Database (GMTED)[48]. The original layer (30 arc seconds resolution) was also upscaled to 10 arc minutes resolution (~20 km). Slope was kept constant at future time periods. Current and future environmental information was extracted for each crop and wild relative occurrence record using the extract function of the raster package[40] in R.

Climatic niche analyses. Principal component analyses (PCAs) were run to plot each species' occurrences in climatic spaces made of the two first principal component axes, summarizing the variation in the nine bioclimatic and slope variables given previously. PCAs were performed using the ade4 package[49] in R. To identify and represent each species' niche, we drew a convex polygon around the occurrence points in the climatic space using the chull function of the grDevices package[50] and several functions of the sp package[51] in R. Several techniques quantifying niches have been highlighted in the literature (for example, range box, generalized additive models and MaxEnt)[52]. We used the convex hull because (1) it does not rely on point density, (2) the algorithm's performance is case-specific and dependent on the quality of the input data and tested hypotheses[53], (3) it favours sensitivity over specificity and therefore targets an overestimate of the niche that we believe is of most relevance to the context of this study and, more generally, for large-scale agricultural applications and (4) it is relatively simple conceptually and hence easily interpretable[54]. Given that the sampling of occurrence points in this study is particularly uneven in both geographic and climatic spaces, relying on point density would lead to a strong bias towards highly sampled areas. The use of convex polygons is, however, sensitive to outliers. As some of our outliers may be due to previously unidentified sampling errors (for example, poor geolocation, botanic gardens' coordinates and so on), we repeated our analyses with six different selections of outliers for each species. This selection was based on the Mahalanobis distance of each occurrence point within the niche space defined by the PCA[55]. Six distance thresholds (distance values of 5 to 10) were then selected based on previous visual inspections (Supplementary Fig. 9).

We estimated the current sub-Saharan climatic niches of the 29 crops using the occurrence records for each of these in the Afrotropics. In the same climatic space, we also estimated the range of climatic conditions expected for 2050 and 2070 at the current locations of cultivation of the 29 crops (hereafter, 'future climatic conditions'). To obtain an estimate of how much climatic conditions are expected to change in the future in the locations where the 29 crop species are currently found in SSA (that is, the security measure), we measured the overlap between the current and future climate spaces for each crop species. The overlap was measured as the percentage of the total area of the polygon representing the future climatic conditions that is intersected by the polygon representing the current niche. In total, 336 measures of overlap were obtained for each crop species as 336 future climate conditions were estimated based on two future time periods, 14 GCMs, two RCPs and six outlier selections. Medians, means and 95% confidence intervals were computed across these different combinations to obtain single consensus values for each crop and/or future climatic scenario.

The expected future climate space that is not currently occupied by a crop (hereafter, 'new climate') may represent particularly high insecurity for its cultivation. Therefore, we isolated the area of the future climate space polygon not covered by the current niche polygon and assessed whether (1) the same crop is occupying this climatic space in other continents (adaptive strategy 1), (2) its wild relatives are occupying this climatic space somewhere across the world (adaptive strategy 2) and (3) the other 28 crops are occupying this climatic space in SSA (adaptive strategy 3). For the first adaptive strategy, we estimated the percentage of the new climate polygon area of the crop that overlaps with the current climatic niches of the same crop in each biogeographic realm of the world, except the Afrotropics and Antarctica (that is, Nearctic, Neotropic, Palaearctic, Indomalay, Australasia and Oceania). We also obtained an overlap measure by aggregating the six different regions' polygons into one by using the aggregate function from the sp package[51] in R. For the second adaptive strategy, we estimated the percentage of the new climate polygon area of the crop that intersects with the current global climatic niches of each of its wild relatives and of all of them aggregated together. For the third adaptive strategy, we estimated the percentage of the new climate polygon area of the crop that overlaps with the current climatic niches of each of the other 28 crops in the Afrotropics used in this study and of all of them aggregated together. For each adaptive strategy, medians, means and 95% confidence intervals of the overlap values were obtained for each crop and/or future climatic scenario across different GCM × RCP × outlier selection combinations. Mean overlap values of the different biogeographic realms (adaptive strategy 1) and crop wild relatives' gene pools (adaptive strategy 2) were then compared by performing Kruskal–Wallis tests and post hoc tests for multiple comparisons using the kruskalmc function of the pgirmess package[56] in R. No overlap value was assigned to a particular gene pool/biogeographic realm if the species had no wild relative/crop occurrence from that gene pool/biogeographic realm ($N_{\mathrm{genepool1}} = 15$, $N_{\mathrm{genepool2}} = 23$, $N_{\mathrm{genepool3}} = 21$, $N_{\mathrm{genepool4}} = 4$). Individual PCAs were run for each of the three strategies, 29 crops and 336 measures of overlap. The two first axes of these PCAs explained 65.9 ± 3.6% of the variance in the environmental data (Supplementary Table 6). The methodological framework of this study is represented in Fig. 1.

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

The data that support the findings of this study are available from several databases listed in the Methods of the manuscript. Data are available from the authors on reasonable request and following data restrictions from these databases.

Code availability

The main R functions and packages used in this study are provided in the Methods. Full R scripts are available from the authors on reasonable request.

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The data that support the findings of this study are available from several databases listed in the Methods section of the manuscript. Data are available from the authors upon reasonable request and following data restrictions from these databases.

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Study description	Using >200,000 worldwide occurrence records for 29 major crops and 778 of their wild relative species, we assess for each crop how future climatic conditions are expected to change in SSA and whether populations of the same crop from other continents, wild relatives around the world, or other crops from SSA are better adapted to expected future climatic conditions in the region. We used multivariate analyses (Principal Component Analyses) and convex hulls based on all occurrence records available for the 29 crops and 778 crop wild relatives, and several climatic scenarios for years 2050 and 2070 (14 Global Circulation Models and 2 Representative Concentration Pathways). Further additional analyses were conducted in order to investigate variation through time and across the different climatic scenarios, and to identify regions of the world, gene pools of crop wild relatives, or crop species from Sub-Saharan Africa that could provide more solutions to agriculture in Sub-Saharan Africa under future climate change. To assess this point, we conducted several mean/median comparisons.
Research sample	We studied 29 different crop species and 778 of their wild relatives (Supplementary Tables 1-2). Most crops are food crops but some are industrial (e.g. cotton). Out of the 29 crops, 27 genera are represented given the presence of two yam species (Dioscorea rotundata-cayenensis complex and D. alata), and two coffee species (Coffea arabica and C. canephora). The crops comprise different life forms (trees, shrubs, herbs, vines) and longevities (annuals, perennials). The identity of 967 wild relative species of the 29 crops was therefore retrieved from the project "Adapting agriculture to climate change: collecting, protecting and preparing crop wild relatives" (https://www.cwrdiversity.org) in November 2016. As part of this project, each wild relative was assigned a degree of relatedness to its associated crop following a four genepool classification, with the species from the primary gene pool considered to be more closely related to the crop and therefore easier to breed with it than the species from the fourth. We used this classification because (i) it is based directly on plant crossing ability and past utility and (ii) complete phylogenies are not available for many of our species of interest. Finally, it is important to note that the 778 species are considered wild relatives in a broad sense given that some of them may have also been partly domesticated.
Sampling strategy	The 29 crop species were chosen if: 1) they were known to be cultivated relatively widely in Sub-Saharan Africa (SSA) according to both the FAO16 and experts from Royal Botanic Gardens Kew, UK and the Council for Scientific and Industrial Research (CSIR), South Africa, 2) reliable and numerous occurrence data were available across their known distribution in SSA, and 3) their wild relatives could be identified. Because of the relatively poor taxonomic and geographic quality of infra-specific/hybrid data, we decided to work at a species level for both crops and wild relatives. We discarded 189 out of the 967 species as these did not have the minimum three occurrences necessary for conducting climatic niche analyses. We therefore considered all wild species known to be related to the 29 crops, except those lacking geographic information.
Data collection	N.K. obtained original species lists. S.P. and J.B. collated and cleaned species occurrence records from online databases (GBIF, CWR diversity, Rainbio, Genesys, and agricultural surveys) and therefore obtained the final list of species for analysis. S.P. and I.O. collected climatic and topographic data from the CHELSA database and the Global Multi-resolution Terrain Elevation Database (GMTED), and resampled the different layers at a 10 arc-min resolution.
Timing and spatial scale	Occurrence records were downloaded in May 2017. They were collected previously by different institutions from 1950 to 2017. Climatic and topographic data are given for the 1979-2013, 2040-2060, and 2060-2090 periods, and were downloaded in January 2019.
Data exclusions	We discarded species for which no geographic data was available. The use of convex hulls for quantifying species climatic niches is sensitive to outliers. As some of our outliers may be due to previously unidentified sampling errors (e.g. poor geolocation, botanic gardens' coordinates…), we repeated our analyses discarding six different selections of outliers for each species. This selection was based on the Mahalanobis distance of each occurrence point within the niche space defined by the PCA. Six distance thresholds (distance values of five to ten) were selected based on previous visual inspections.
Reproducibility	Re-running the code provided the same output. It was therefore successful.
Randomization	This does not apply here. We quantified observed climatic overlaps among species/populations rather than testing for the effect of a variable/treatment on species/populations.
Blinding	This does not apply here as for randomization.

Did the study involve field work? ☐ Yes ☒ No

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