Agricultural Systems 202 (2022) 103464

Contents lists available at ScienceDirect

Agricultural Systems

journal homepage: www.elsevier.com/locate/agsy

Strategizing research and development investments in climate change adaptation for root, tuber and banana crops in the African Great Lakes Region: A spatial prioritisation and targeting framework

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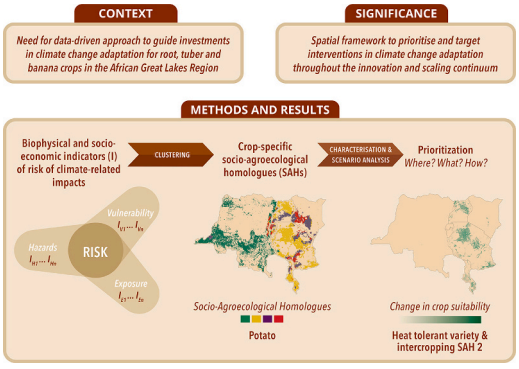
HIGHLIGHTS

- Dta-driven approach to guide climate change adaptation for root, tuber and banana crops in the African Great Lakes Region
- Clusters of homologous regions (SAHs), defined by the risk of climate-related impacts, were developed
- Four SAHs were identified for each of banana, potato and sweetpotato and five for cassava.
- The potential of genetic and agronomic innovations for mitigating impacts in prioritised SAHs was demonstrated
- Spatial framework to prioritise and target interventions throughout the innovation and scaling continuum

GRAPHICAL ABSTRACT



ARTICLE INFO

Keywords:
Prioritisation
Targeting
Climate smart agriculture
Climate risk
Roots, tubers and bananas
Climate hotspots

ABSTRACT

CONTEXT: Given the significance of climate change impacts on farming communities, large investments are made by research and development actors, including farmers themselves, to adapt agricultural systems. A data-driven approach is required to guide these investments and maximize their impact. In the African Great Lakes Region (GLR), root, tuber and banana (RT&B) crops are a vital component of smallholder farming systems, but little is known about strategies to mitigate climate change impacts on these crops.

OBJECTIVE: The objective of this study was to develop a spatial prioritisation and targeting framework based on the risk of climate-related impacts to guide research investments and prioritisation in CSA for RT&B crops in the GLR.

METHODS: Climate change impact data on crop suitability were layered onto other spatially-explicit biophysical and socio-economic data to map clusters of homologous regions, called socio-agroecological homologues (SAHs). The SAHs were defined by the risk of climate-related impacts, resulting from the interaction of hazards,

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https://doi.org/10.1016/j.agsy.2022.103464
Received 28 February 2022; Received in revised form 26 June 2022; Accepted 13 July 2022
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exposure and vulnerability. The framework was applied to RT&B crops (banana, potato, cassava and sweetpotato) in the African GLR. Its utility was illustrated by elaborating adaptation scenarios for selected SAHs of one long-duration (banana) and one short-duration (potato) RT&B crop.
RESULTS AND CONCLUSION: Four SAHs were identified for banana, potato and sweetpotato and five for cassava. For each crop, SAHs were prioritised for investment in climate change adaptation based on the level of risk of climate-related impacts. Scenario analysis showed that the introduction of drought-tolerant varieties would increase suitability for banana from 0.30 to 0.47 under baseline conditions and from 0.54 to 0.71 under future climates in a prioritised SAH with low to moderate suitability for typical varieties. For potato, the introduction of heat-tolerant genotypes, intercropping with legumes or the combination of both would allow compensating negative impacts of climate change on crop suitability in two SAHs representing important mid-altitude potato growing areas, from an average of −0.19 and −0.16 to an average of up to +0.25 and + 0.15 respectively. Scaling approaches should consider the difference in socio-economic conditions between the two SAHs.
SIGNIFICANCE: We envision the framework to be useful for a diverse range of users throughout the innovation and scaling continuum to understand where climate change impacts are expected to be most severe, what type of innovations are needed to help farmers adapt, and how these innovations should be scaled to enable uptake by considering socio-economic drivers of adoption.

1. Introduction

The majority of the African Great Lakes Region's (GLR) population relies on smallholder agriculture for food security, income, and livelihoods. Root, tuber, and banana (RT&B) crops are a vital component of farming systems in the region, covering >27% of the cropped area (FAOSTAT, 2021) and providing up to 47% of the daily caloric intake (Thiele and Friedmann, 2020). Despite the importance of RT&B crops, little is known about the potential effects of climate change on these crops and strategies to mitigate impacts (Manners and van Etten, 2018; Petsakos et al., 2019). A recent study by Manners et al. (2021) demonstrated that the impacts of climate change on the environmental suitability of the GLR for RT&B crops will be somewhat favourable, except for potato which will be negatively affected throughout most of the region due to rising temperatures. However, Manners et al. (2021) also showed that the change in the environmental suitability will vary substantially across the GLR, due to the diversity in agroecological conditions.

Safeguarding and enhancing food and nutrition security under changing climates requires adaptation strategies including climate-smart agricultural practices that are tailored to agroecological diversity and socio-economic contexts. In the farming systems of sub-Saharan Africa (SSA), substantial research and development investments are made in climate-smart agriculture (CSA) to reduce risks and increase resilience of smallholders. To maximize their impact, it is important to prioritise and guide these investments (Thornton et al., 2018) by considering *where* climate change adaptation is most needed, *what* type of innovations are required to address constraints and increase resilience of smallholder farmers, and *how* these innovations should be made available and promoted to enable uptake by farmers.

As elaborated by IPCC, the risk of climate-related impacts results from the interaction of (i) hazards: the potential occurrence of climate-related physical events or trends or their physical impacts, (ii) exposure: the presence of people, livelihoods, species or ecosystems, environmental functions, services, and resources, infrastructure, or economic, social, or cultural assets in places and settings that could be adversely affected, and (iii) vulnerability: the propensity or predisposition to be adversely affected, including sensitivity or susceptibility to harm and lack of capacity to cope and adapt (Fig. 1). Hence, besides being driven by hazards resulting from biophysical variables related to climate, the risk of climate-related impacts is shaped by socio-economic processes, and the result of a dynamic interplay between socio-economic pathways,

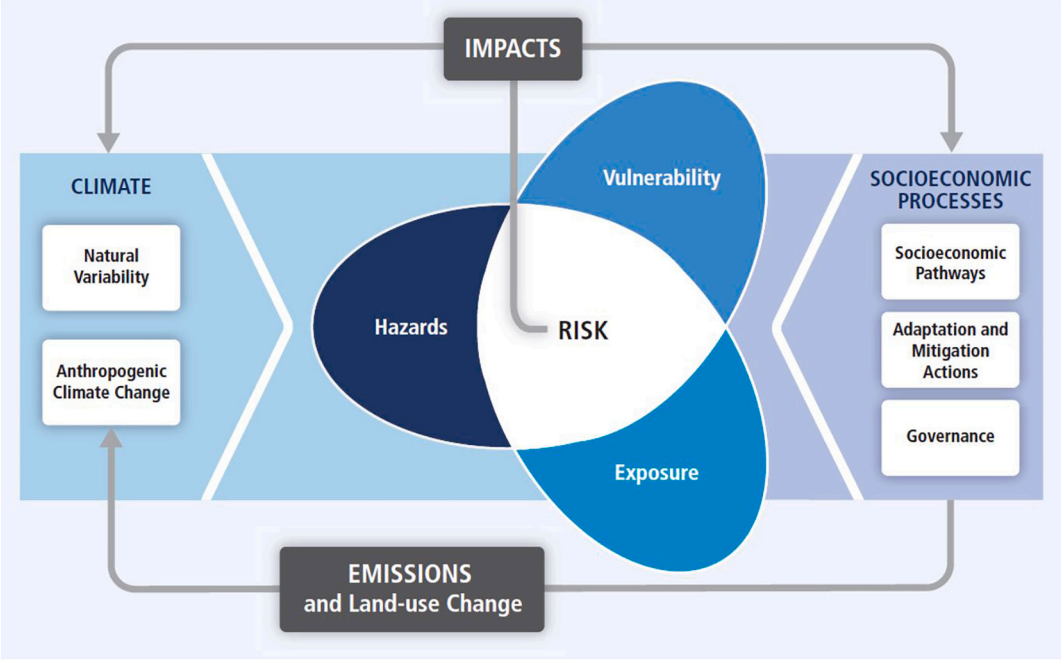

Fig. 1. The risk of climate-related impacts arising from the interaction of climate-related hazards, exposure and vulnerability (IPCC, 2014).

adaptation and mitigation actions, and governance structures supporting or hindering the capacity to take up these actions (Working group II AR5, IPCC, 2014). Prioritisation of *where* to invest in climate change adaptation should be based on the *level of risk* farming communities are likely to face, while prioritisation of *what* kind of innovations to invest in and *how* to scale them should be based on understanding the *characteristics of risk* (type of hazards, e.g. drought/ heat, and socio-economic features of the farming populations). Hence, for prioritising where to invest in what and how, both biophysical and socio-economic variables should be considered, including the socio-economic contexts affecting adoption potential of innovations.

One approach that has been used to gain insights into what and where innovations are likely to be needed and effective is the delineation of mega-environments (Crespo-Herrera et al., 2021). Mega-environments have been defined as broad, not necessarily contiguous areas occurring in more than one country, defined by similar biotic and abiotic stresses, cropping-system requirements, consumer preferences, and volume of production (Rajaram et al., 1994). They have been used to manage genotype by environment interactions and guide planning of varietal delivery (Hartkamp et al., 2000). A comparable approach has been used for the scaling out of agronomic solutions through Technology Extrapolation Domains (Rattalino Edreira et al., 2018; Andrade et al., 2019).

Mega-environments have been largely based on agro-climatological variables, such as daylength, temperature, and precipitation (Hartkamp et al., 2000). A similar concept with a greater emphasis on socio-economic contexts is recommendation domains, which are relatively homogenous geographical areas in terms of biophysical and socio-economic characteristics that are relevant for agricultural innovation (Muthoni et al., 2017; Notenbaert et al., 2013; Omamo et al., 2006). As for mega-environments, recommendation domains can cross national and other administrative borders, hence providing an opportunity to address issues and constraints through regionally coordinated agricultural development efforts (Omamo et al., 2006).

In this study, a spatial prioritisation and targeting framework that explicitly integrates indicators of the risk of climate-related impacts in recommendation domains is proposed. It is applied to provide proof-of-concept to guide research investments and prioritisation in CSA for RT&B crops in the GLR. The framework is based on crop-specific, socio-agroecological homologues (SAHs), defined as clusters of geographies with broadly similar risks of climate-change related impacts, determined by the interaction between hazard, exposure, and vulnerability. We aim to demonstrate how the framework can facilitate the development of both short- and long-term adaptation strategies that transcend administrative boundaries and are tailored to the socio-economic contexts in which farmers operate.

2. Materials and methods

In this section, we conceptualize the spatial prioritisation and targeting framework and how it can be used for wider application. We also describe its application in the specific context of a case study, RT&B crops in the GLR.

2.1. Region and crops

This study focused on the four most important RT&B crops in the GLR of Africa, banana (*Musa spp*), cassava (*Manihot esculenta*), potato (*Solanum tuberosum*), and sweetpotato (*Ipomoea batatas*). The GLR region consists of seven countries (Burundi, the Democratic Republic of the Congo, Kenya, Malawi, Rwanda, the United Republic of Tanzania, and Uganda) that border the African Great Lakes.

2.2. Indicators of risk (hazards, exposure, vulnerability) for constructing socio-agroecological homologues

To identify regions with similar risks of climate-related impacts for each crop, we generated clusters of geographies with broadly similar biophysical and socio-economic characteristics indicative of climate-related hazards, exposure, and vulnerability under climate change. For this study, we selected three indicators of hazards, three of exposure, and two of vulnerability, respectively. It is important to note that the choice of the indicators is adaptable to specific objectives of users of the framework and can be altered for future iterations of the framework in the same context or entirely new applications in other contexts. An overview of selected indicators for the application of the framework in the context of the case study presented in this paper with a justification and details on their data sources is provided below.

2.2.1. Hazards

For the indicators of hazards, we built on an earlier study where the environmental suitability of the GLR was modelled for the RT&B crops of interest (Manners et al., 2021). Manners et al. (2021) used an adapted EcoCrop model to estimate environmental suitability for crops (crop suitability) at a 1 km^2 resolution under baseline (average of 1970–2000) and future (2040–2060s) climate conditions under a high but plausible greenhouse gas emission scenario (RCP 6.0). EcoCrop analyses the suitability of an environment for a crop by comparing climatic data with crop-specific optimum and absolute ranges for minimum temperature, average temperature, and precipitation, and provides a suitability value (ranging from 0 = not suitable to 1 = highly suitable) based upon how suited climatic conditions are relative to the crop-specific ranges (Manners et al., 2021). Future downscaled climate data were sourced from the database of the CGIAR Research Program on Climate Change, Agriculture, and Food Security (CCAFS; Ramirez and Jarvis, 2010). Data layers were assembled for the 15 available global circulation models (GCMs). More details on the methodology that was used to generate spatially-explicit crop suitability data is provided in Manners et al. (2021). Three indicators were derived from these data:

- *Baseline crop suitability (value between 0 = not suitable and 1 = highly suitable)*: This is the crop suitability under baseline climatic conditions. It is an indicator for climate-related hazards that farmers are likely to face under current climatic conditions.
- *Future change in crop suitability (value between − 1 = maximum reduction in suitability and + 1 = maximum increase in suitability)*: This is the change in crop suitability under future relative to baseline climatic conditions. Farmers are at higher risk of climate-related impacts on their livelihoods in areas where crop suitability of the crops they rely on will be negatively affected by climate change. Conversely, where suitability is positively affected there is an opportunity to expand areas or increase production on land already cultivated with the crop.
- *Future crop suitability limiting factor (minimum temperature, average temperature, seasonal precipitation, or precipitation during key growth periods)*: This is the environmental variable that is most limiting to crop suitability under future climates in a given environment, as estimated by the model. It reflects the type of climate-related hazard farmers are likely to face. The crop suitability limiting factor informs the type of innovations that are needed to adapt to climate change.

2.2.2. Exposure

- *Population density (1000s/km^2)*: Population density is an indicator for the number of people that are likely to be affected by climate-related impacts in a given location. Population density also affects average farm size, which in turn influences agricultural practices and may determine the rate of technological adaptation (Andrade et al.,

2019). Population density data at a 1 km^2 resolution were collected from CIESIN (2017) for the year 2015.

- *Current area under production (ha/10km²)*: We assumed that exposure to climate-related impacts on a specific crop is higher in places with a larger area under production of this crop. Data on harvested area per crop were extracted from the Spatial Production Allocation Model dataset (IFPRI, 2019), which were available at a resolution of 4.5 arc minutes for the year 2010. The data were then disaggregated to 30 arc *sec* (~1 km^2), using the raster package of R (Hijmans, 2021).

2.2.3. Vulnerability

- *World Governance Index*: Poor governance inhibits farmers to effectively adapt and cope with climate change. The World Governance indicators, developed by the World Bank, provide an estimate of a country's governance quality across six indicators: voice and accountability, political stability, government effectiveness, regulatory quality, rule of law, and control of corruption (World Bank, 2019). Values range from 0 (poor) to 1 (good) for each indicator. To generate a comprehensive indicator of governance, we developed an average of these national indicators to create a World Governance Index, with one value per country. These national values were converted into a 1 km^2 raster layer. Data were collected for the year 2015.
- *Human Development Index (HDI)*: The HDI combines income, education, and health indices to provide a comprehensive indicator of the human and financial capital available in a region, which affects the capacity to adapt to climate change. Recent developments have seen the publication of subnational HDI values (Smits and Permanyer, 2019). These data were collected at administrative level as (subnational) shapefiles and converted to a 1 km^2 raster for the year 2015.
- *Travel time to urban areas (hours):* The travel time to urban areas affects market access. Farmers are more likely to invest in adaptive innovations when there are good market opportunities. In addition, market access affects access to inputs (Corbeels et al., 2014; Shiferaw et al., 2009). Data on travel time to urban areas, for the year 2015, was collected at a 1 km^2 resolution from Weiss et al. (2018) and converted from minutes to hours in R.

Inclusion of contemporary, rather than projected, socio-economic data was deemed appropriate as we assumed that the socio-economic conditions of the present will determine the capacity to gradually adapt to future climates.

All socio-economic data were cropped to an area of 5.4°N to 17.1°S and from 12.2 to 41.9°E, covering all GLR countries, and clipped to correspond with defined croplands of 2015 (Xiong et al., 2017). Maps showing the variation of the individual indicators across the region are shown in Supplementary Information (Fig. S1).

2.3. Socio-agroecological homologue development and analysis

To generate clusters of geographies that are homologous for the selected indicators, we used standard cluster analysis routines for each crop to generate crop-specific SAHs. All analyses were performed in R (R Core Team, 2021).

We performed a simple correlation analysis between all the variables, using the rcorr function in R (Harrell, 2020) to identify whether any of the selected indicators could be dropped because of collinearity. As no significant correlations were identified, the eight indicators were retained.

Data from raster layers of each indicator were extracted into a matrix and scaled. A randomly selected sub-sample, representing ~15% of all analysed cells, was taken to determine the ideal number of clusters. The sub-sample was necessary due to the computing limitations of the clustering methodology. The optimal number of clusters was identified using NbClust (Charrad et al., 2014). NbClust provides 30 unique indices for determining the most optimal clustering scheme (number of clusters) – the scheme with the largest number of indices.

CLARA (Clustering Large Applications) was implemented using the homonymous function of the cluster package in R (Kaufman and Rousseeuw, 1990; Maechler et al., 2021). CLARA applies the partitioning around medoids algorithm on multiple samples of a dataset, identifying optimal medoids, based upon the desired number of clusters, and assigns each observation (in this case land area cell) to a cluster based upon these optimal medoids (Kaufman and Rousseeuw, 1990). CLARA was implemented on the full, rather than sub-sampled, dataset. The cluster designation for each land area cell was defined as the respective SAH. These outputs were later converted into a raster format.

Summary statistics were determined for the constituent variables of the homologues (indicators) and for other variables deemed relevant to their interpretation, related to the climatic conditions and the size of the SAH. These additional variables were total annual rainfall, total annual rainfall change between the baseline and future climate, average annual temperature, average temperature change between the baseline and future climate (Fick and Hijmans, 2017; Ramirez and Jarvis, 2010), elevation (USGS, 2020) and percentage of total cropped area in the GLR (IFPRI, 2019). For continuous variables, medians across cells were calculated within each SAH. For categorical variables, we extracted the modal value for each SAH.

2.4. Prioritising and targeting R&D investments in climate change adaptation

2.4.1. Where?

SAHs where crop suitability for target crops will change considerably, either negatively or positively, are potential candidates to be selected for R&D investments towards climate change adaptation of smallholder farmers. SAHs with currently high but decreasing suitability and a high importance of the crop (high hazard and high exposure) can be selected for investments in breeding and agronomy to target or develop more climate-smart varieties and agronomic practices. SAHs with an increasing crop suitability under climate change can be selected for interventions aiming at expansion or promotion of a crop, especially where crop suitability of other major crops is negatively affected. A decision to prioritise a certain SAH for greater investment may also be based on socio-economic conditions driving exposure or vulnerability and the expected impact on livelihoods.

2.4.2. What?

Hypotheses on *what* kind of climate-smart technologies or practices are likely to alleviate climate-induced hazards can be formulated based on the biophysical characteristics of prioritised SAHs. Scenario analysis can then be conducted based on evidence of how negative climate change effects on crop suitability are mitigated by specific technologies or practices. This can include germplasm-based scenarios (introducing more climate-smart varieties), agronomy-based scenarios (introducing climate-smart agronomic practices) and combinations of both. The adapted EcoCrop model for estimation of crop suitability allows for considering such scenarios by either changing environmental niche ranges for crops (e.g. in the case of adapted varieties or agronomic practices like irrigation that reduce precipitation requirements) or altering the environmental variables (e.g in the case of agronomic practices that affect the micro-climate in crop fields). Evidence on the effect of technologies and practices on crop and environmental parameter can be derived from scientific publications, which are increasingly available and have recently been brought together in a dynamic meta-dataset 'Evidence for Resilient Agriculture (ERA)' (era.ccafs.cgiar.org). This dataset includes data on the performance and effects of a range of agricultural technologies and practices, including genetic improvements, soil, residue and water management, irrigation and cropping systems options, on productivity, resilience and climate change mitigation outcomes.

To illustrate the potential application of the framework in a concise manner, we developed and tested a suite of scenarios for one long-duration (banana) and one short-duration (potato) RT&B crop.

For banana, the potential effect of the introduction of improved drought tolerant varieties on baseline and future suitability was assessed according to Manners et al. (2021). In addition, the potential effect of mulching was evaluated by assuming that with mulching the seasonal precipitation requirement of banana is reduced by 10%. This is a conservative assumption based on the results of Salau et al. (1992) who demonstrated that soil moisture content is at least 10% higher, on average throughout the year, and 15–50% higher during the peak dry season, when banana is mulched with elephant grass compared to a control without mulching. Environmental niche ranges used in crop suitability modelling were adapted for this scenario according to Manners et al. (2021).

For potato, the potential effect of three scenarios on future suitability was investigated (i) the introduction of heat-tolerant varieties, ii) intercropping potato with legumes, and iii) a combination of both heat-tolerant varieties and intercropping. The method described by Manners et al. (2021) was used to determine the potential impact of introducing heat-tolerant varieties on crop suitability. For the intercropping scenario, we assumed that in-canopy temperature is at least 3° Celsius lower under a potato-legume intercrop compared to monocropping, based on the results of Nyawade et al. (2019) who showed that intercropping potato with legumes in mid-altitude areas reduces soil temperature with 2–6° Celsius, favouring tuber development in these relatively warm environments. To simulate the effect of this reduction in temperature, average temperature in the environmental input data to the crop suitability model was decreased by 3° Celsius relative to above-canopy air temperatures.

2.4.3. How?

The 'How?' refers to the enabling conditions for the uptake of climate-smart technologies and practices. The socio-economic characteristics of the prioritised homologues can guide choices among a suite of adaptation options based on expected drivers of adoption and inform strategies for successful dissemination and scaling.

To understand potential of and constraints to adoption, first the risk itself (and how it may promote or hinder adoption) in prioritised SAHs should be considered. Although farmers who face or perceive higher levels of risk may be less willing or able to innovate, the occurrence of climate risks may also encourage farmers to participate in agricultural innovation activities and invest in adaptation as a risk mitigation strategy (Lemessa et al., 2019; Mubiru et al., 2018). In addition, factors potentially affecting adoption reflected in the indicators (components) of risk can be considered, such as land size and labour availability (reflected in population density), market access (reflected in travel time to urban areas), expected level of extension support (reflected in WGI) and financial and human capacity to innovate (reflected in HDI).

For creating enabling conditions for uptake of CSA technologies and practices, a broad range of complementary technical and institutional innovations can be brought into the picture such as value chain development, aggregation, seed system development, price mechanisms, and even innovations directly associated with climate change adaptation such as bundling with crop insurance and the provision of climate services. This can also include enabling policies such as subsidized inputs or credits, investments in local extension, investment in infrastructure (e.g. irrigation) and information and communication systems, or seed regulatory and distribution frameworks. In addition, the CSA technologies and practices itself, as well as the extension models and the selection of scaling partners can be tailored to the socio-economic context of the SAHs.

3. Results

3.1. Characterization and prioritisation of socio-agroecological homologues ('where?')

One SAH for cassava and two for sweetpotato were very small in total size (<1% of cropped area) and were therefore dropped for further analysis (and not shown in Tables and Figures). Fig. 2 shows the spatial distribution of the retained SAH's: four SAHs for each of banana, potato and sweetpotato, and five SAHs for cassava. Tables 1 to 4 provide summary statistics for the indicators of hazard, exposure, and vulnerability considered in the cluster analysis, as well as other variables relevant to the interpretation of the SAHs. Table 5 provides a summary of the level of climate-related hazard and exposure and vulnerability to climate change in each of the crop-specific SAHs.

For banana, two SAHs (1 and 4) had very high suitability under both baseline and future climates (Table 1). SAH 2 is interesting because it has low suitability for banana while representing a fairly high area under banana production and having medium to high population density (Table 1). Suitability in this SAH is expected to improve yet remains relatively low under future climates. Moreover, the improved suitability in this SAH is driven by an increase in precipitation, which is low in absolute terms (Table 1) and may be offset as rains become less reliable. This SAH may therefore be prioritised for R&D investments in climate-smart agriculture in banana systems. SAH 2 includes large areas in Tanzania, Kenya and Malawi and some smaller areas in Uganda, Rwanda, Burundi and DRC (Fig. 2).

For cassava, SAH 1, 2, and 4 have high suitability under both baseline and future climates (Tables 2, 5). Among all SAHs for cassava, SAH 3 has the lowest suitability under baseline and future climates (driven by low temperatures), and the area under production is consequently very low, hence farmers rely on other crops for their livelihoods. Suitability for cassava in SAH 5 is moderate and limited by precipitation during a key growth period of cassava (the crop establishment stage, Manners et al., 2021). It also has a relatively large area under production and represents 25% of the total cropped area in the GLR (Table 2). Suitability under future climate in this SAH will however increase to high levels (mean = 0.86). Climate-smart innovations such as varieties that are better able to cope with drought at early stages may benefit cassava production under baseline climates in SAH 5.

Potato is the only RT&B crop included in this study that will see a negative change in suitability in some of the potato SAHs identified, due to rising temperatures (Table 3). Although SAH 1 has a high climate-related hazard for potato production, it also has a very small area under production due to low suitability under baseline climates, therefore exposure to climate change is low in this SAH. SAH 2 and 3 both have moderate to high suitability under baseline climates which is expected to decrease under climate change. The main difference between SAH 2 and 3 is the level of vulnerability to climate change which is higher in SAH 2 (relatively remote areas in Uganda, Tanzania and Malawi with a lower HDI and WGI and higher travel time to urban centers compared to SAH 3) (Fig. 2). Both SAH 2 and 3 can be prioritised for R&D investments in climate change adaptation.

For sweetpotato, three SAHs (1, 3 and 4) show a very high suitability for sweetpotato both under baseline and future climates. SAH 2 is the only homologue where climate-smart agriculture and climate adaptation of sweetpotato production may be needed. Suitability for sweetpotato in this SAH is relatively low driven by suboptimal precipitation. Mean levels of seasonal precipitation will increase under climate change driving a positive change in suitability, but this increase in precipitation is relatively low in absolute terms (<100 mm), much of which could be lost through evaporation or evapotranspiration. Also, this increase may easily be accompanied by more erratic precipitation patterns associated by climate change. SAH 2 includes 20% of the total cropped area in the GLR (Fig. 2) with a considerable area under sweetpotato production, and in general has moderate levels of both exposure and vulnerability to

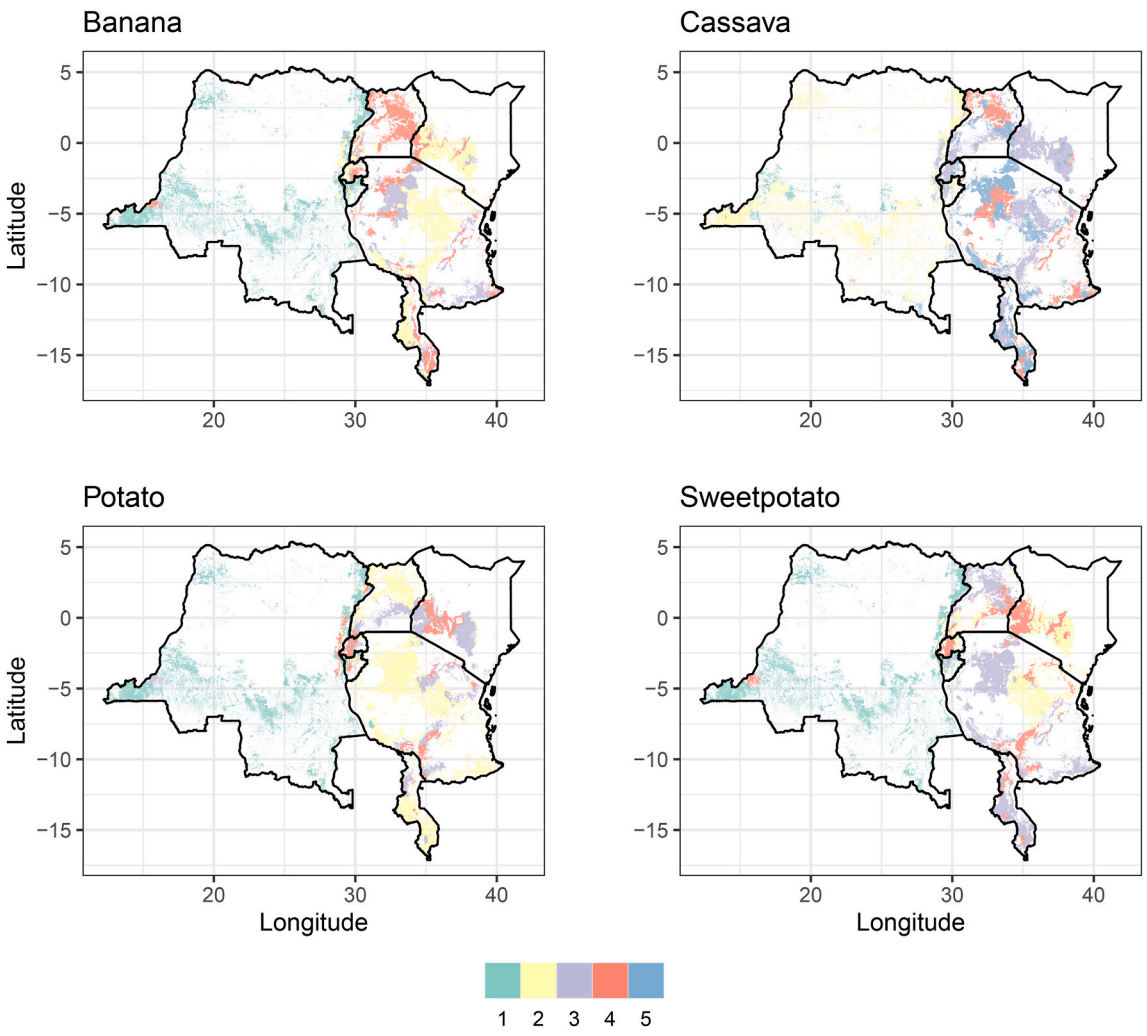

Fig. 2. Socio-agroecological homologues (SAHs) for banana, cassava, potato and sweetpotato in the Great Lakes Region of Africa. Different colors represent different SAHs specific to each crop (there is no relation between SAHs with same colour of different crops). Horizontal and vertical axes indicate longitude and latitude, respectively.

climate change. Hence, this SAH can be prioritised for R&D investments towards climate-smart agriculture options to cope with drought stress, under both baseline and future conditions.

3.2. Assessing promising adaptation options ('what?' and 'how?')

Previously (section 3.1), crop-specific SAHs were prioritised for R&D investments in climate-smart agriculture for each of the RT&B crops considered in this study (prioritisation of '*where*'). In this section, we evaluate what type of interventions or investments could be most effective to address climate-induced stresses in these prioritised SAHs ('*what?*'), and how enabling conditions for uptake can be created ('*how?*'), for one long-duration (banana) and one short-duration (potato) RT&B crop.

Fig. 3 shows suitability for banana in SAH 2 (precipitation-limited) under 4 scenarios: (i) baseline climatic conditions using typical banana varieties, (ii) baseline climatic conditions using drought-tolerant banana varieties, (iii) future climatic conditions using typical banana varieties, and (iv) future climatic conditions using drought-tolerant varieties. With the use of typical varieties, mean suitability for banana is as low as 0.30 under baseline climates, increasing to 0.54 under future climates because of a modest increase in precipitation. With the introduction of drought-tolerant varieties, suitability could increase to 0.47 under baseline and 0.71 under future climates (Fig. 3). Through mulching, suitability would increase to 0.38 under baseline and 0.63 under future climates (data not shown).

For potato, reductions in suitability as a result of climate change can be reversed by the introduction of heat-tolerant potato varieties, from an average of −0.19 and − 0.16 to an average of +0.05 and + 0.04, for SAH 2 and SAH 3, respectively (Fig. 4). In other words, the introduction of heat-tolerant varieties will compensate the projected reduction in suitability under climate change. Similarly, the practice of intercropping potato with legumes is able to fully compensate the reduction in suitability under climate change and will result in further increases in suitability (average of +0.12 and + 0.09 for SAH 2 and SAH 3, respectively) compared to monocropped potato under baseline climatic conditions. When heat-tolerant varieties are combined with intercropping, suitability under future climates will increase even further with +0.25 and + 0.15 compared to the baseline scenario for SAH 2 and SAH 3, respectively (Fig. 3).

Table 6 provides examples on how strategies for introducing new climate-smart varieties or agronomic practices like mulching and intercropping can be informed by the variation in socio-economic conditions of prioritised SAHs. The characteristics of the prioritised SAH for banana suggest moderate levels of land sizes, labour availability, market access and capacity to innovate. A seed system based on a decentralized multiplication model coupled with promotion campaigns by local authorities could favour the adoption of adaptation strategies including

Table 1
Socio-agroecological homologues (SAH) for banana with mean values with their standard deviations (SD) for indicators of hazard, exposure and vulnerability, and other relevant variables. Future conditions refer to projected changes by 2050.

	SAH	Hazard			Exposure		Vulnerability			Other relevant variables						
		Baseline suitability	Suitability change	Future limiting factor (modal)	Population density (1000s/km^2)	Area under production (ha/km^2)	HDI	WGI	Travel time to urban areas (min)	Baseline limiting factor (modal)	T Baseline (°C)	T Change (°C)	P Baseline (mm)	P Change (mm)	Elevation (m.a.s.l.)	% of cropped area
Mean	1	0.93	0.03	6	87	1.3	0.45	−1.59	169	6	23.6	1.97	1412	28	747	28
	2	0.30	0.28	3	170	0.9	0.53	−0.54	102	3	19.9	1.89	933	77	1439	34
	3	0.73	0.07	3	102	0.7	0.50	−0.48	148	3	22.8	1.87	968	61	1015	17
	4	0.92	0.04	6	315	5.8	0.51	−0.56	55	6	22.8	1.73	1206	68	1025	21
SD	1	0.18	0.07	NA	151	4.3	0.02	0.06	159	NA	2.0	0.44	217	57	414	NA
	2	0.26	0.27	NA	235	4.4	0.04	0.24	75	NA	2.7	0.58	320	90	465	NA
	3	0.18	0.10	NA	122	3.4	0.03	0.10	95	NA	1.8	0.59	160	70	415	NA
	4	0.12	0.07	NA	708	16.7	0.04	0.21	37	NA	1.5	0.32	202	77	331	NA

HDI=Human Development Index; WGI=World Governance Index; T = Average Temperature; P = Annual Precipitation.
Limiting factor legend: 1 = Average T; 2 = Minimum T; 3 = Seasonal P; 4 = P during key growth period; 5 = Multiple; 6 = No limiting factor (perfect suitability).

Table 2
Socio-agroecological homologues (SAH) for cassava with mean values with their standard deviations (SD) for indicators of hazard, exposure and vulnerability, and other relevant variables. Future conditions refer to projected changes by 2050.

	SAH	Hazard			Exposure		Vulnerability			Other relevant variables						
		Baseline suitability	Suitability change	Future limiting factor (modal)	Population density (1000s/km^2)	Area under production (ha/km^2)	HDI	WGI	Travel time to urban areas (min)	Baseline limiting factor (modal)	T Baseline (°C)	T Change (°C)	P Baseline (mm)	P Change (mm)	Elevation (m.a.s.l.)	% of cropped area
Mean	1	0.93	0.02	3	21	1.47	0.46	−1.51	476	3	24.8	1.85	1510	9.10	498	4
	2	0.85	0.08	3	83	4.00	0.45	−1.59	123	1	23.6	1.95	1394	27	748	23
	3	0.44	0.18	1	223	0.61	0.54	−0.57	88	1	19.6	1.85	1035	85	1499	31
	4	0.90	0.09	6	106	1.53	0.49	−0.53	120	4	24.1	1.75	1045	44	816	15
	5	0.68	0.18	4	154	2.78	0.50	−0.52	94	4	22.0	1.92	994	71	1142	25
SD	1	0.07	0.05	NA	20	1.59	0.03	0.30	165	NA	0.9	0.35	213	52	187	NA
	2	0.17	0.08	NA	111	5.24	0.03	0.09	83	NA	1.8	0.43	220	57	394	NA
	3	0.22	0.06	NA	240	1.20	0.04	0.27	73	NA	2.5	0.47	339	92	453	NA
	4	0.07	0.06	NA	118	1.41	0.03	0.12	92	NA	0.9	0.34	211	64	365	NA
	5	0.13	0.06	NA	162	4.49	0.03	0.22	65	NA	1.4	0.68	240	73	279	NA

HDI=Human Development Index; WGI=World Governance Index; T = Average Temperature; P = Annual Precipitation.
Limiting factor legend: 1 = Average T; 2 = Minimum T; 3 = Seasonal P; 4 = P during key growth period; 5 = Multiple; 6 = No limiting factor (perfect suitability).

Table 3
Socio-agroecological homologues (SAH) for potato with mean values with their standard deviations (SD) for indicators of hazard, exposure and vulnerability, and other relevant variables. Future conditions refer to projected changes by 2050.

	SAH	Hazard			Exposure		Vulnerability			Other relevant variables						
		Baseline suitability	Suitability change	Future limiting factor (modal)	Population density (1000s/km^2)	Area under production (ha/km^2)	HDI	WGI	Travel time to urban areas (min)	Baseline limiting factor (modal)	T Baseline (°C)	T Change (°C)	P Baseline (mm)	P Change (mm)	Elevation (m.a.s.l.)	% of cropped area
Mean	1	0.58	−0.23	1	83	0.01	0.45	−1.58	176	1	23.8	2.03	1407	24	702	27
	2	0.72	−0.19	1	145	0.45	0.49	−0.52	115	1	22.6	1.83	979	58	1050	42
	3	0.84	−0.16	1	254	0.43	0.55	−0.57	78	1	21.2	1.79	1036	83	1204	20
	4	0.98	0.00	6	291	3.46	0.54	−0.66	67	6	16.9	1.84	1223	99	1955	11
SD	1	0.18	0.08	NA	242	0.12	0.02	0.11	160	NA	1.6	0.64	222	54	347	NA
	2	0.16	0.06	NA	377	1.38	0.03	0.20	86	NA	1.7	0.43	242	70	356	NA
	3	0.16	0.07	NA	490	1.26	0.03	0.22	61	NA	1.9	0.41	340	76	381	NA
	4	0.06	0.05	NA	338	6.69	0.05	0.41	60	NA	1.7	0.50	275	119	314	NA

HDI=Human Development Index; WGI=World Governance Index; T = Average Temperature; P = Annual Precipitation.
Limiting factor legend: 1 = Average T; 2 = Minimum T; 3 = Seasonal P; 4 = P during key growth period; 5 = Multiple; 6 = No limiting factor (perfect suitability).

Table 4
Socio-agroecological homologues (SAH) for sweetpotato with mean values with their standard deviations (SD) for indicators of hazard, exposure and vulnerability, and other relevant variables. Future conditions refer to projected changes by 2050.

	SAH	Hazard			Exposure		Vulnerability			Other relevant variables						
		Baseline suitability	Suitability change	Future limiting factor (modal)	Population density (1000s/km^2)	Area under production (ha/km^2)	HDI	WGI	Travel time to urban areas (min)	Baseline limiting factor (modal)	T Baseline (°C)	T Change (°C)	P Baseline (mm)	P Change (mm)	Elevation (m.a.s.l.)	% of cropped area
Mean	1	0.99	0.00	6	84	0.14	0.45	−1.59	170	6	23.4	1.99	1418	28	769	28
	2	0.57	0.16	3	123	0.78	0.53	−0.55	112	3	21.0	1.74	785	95	1267	20
	3	0.98	0.01	6	127	2.06	0.49	−0.50	113	6	22.6	1.89	1036	51	1054	34
	4	0.95	0.01	6	339	0.85	0.55	−0.55	54	6	20.1	1.82	1243	73	1432	17
SD	1	0.04	0.03	NA	147	0.65	0.02	0.05	159	NA	2.2	0.46	212	57	434	NA
	2	0.22	0.11	NA	147	2.12	0.04	0.20	78	NA	2.8	0.37	229	66	524	NA
	3	0.06	0.05	NA	123	4.69	0.03	0.13	84	NA	1.8	0.61	197	71	357	NA
	4	0.09	0.09	NA	312	1.53	0.03	0.26	47	NA	2.6	0.45	276	94	458	NA

HDI=Human Development Index; WGI=World Governance Index; T = Average Temperature; P = Annual Precipitation.
Limiting factor legend: 1 = Average T; 2 = Minimum T; 3 = Seasonal P; 4 = P during key growth period; 5 = Multiple; 6 = No limiting factor (perfect suitability).

Table 5
Level of climate-related hazard and exposure and vulnerability to climate change in socio-agroecological homologues (SAH) for banana, cassava, potato and sweetpotato in the GLR.

SAH	Hazard	Exposure	Vulnerability	Description
Banana				
1	Low	Low	High	Very high suitability, no change in suitability, low population density, remote/rural, low HDI and WGI
2	Moderate-High	Moderate	Moderate	Low but increasing suitability, high altitude area
3	Moderate-High	Low	Moderate	Moderate-high suitability, little change in suitability, rural, moderate WGI
4	Low	High	Low	Very high suitability, no change in suitability, high population density, peri-urban
Cassava				
1	Low	Low	Moderate-High	Very high suitability, no change in suitability, highly remote areas with low population density, low WGI
2	Low	High	Moderate-High	High and increasing suitability, rural, very high production, low WGI
3	Moderate-High	Low	Moderate	Low but increasing suitability, low production area
4	Low	Low	Moderate	Very high suitability under baseline and future climate, rural, moderate WGI
5	Moderate	Moderate	Moderate	Moderate and increasing suitability, rural, moderate production are, moderate population density
Potato				
1	High	Low	High	Low and decreasing suitability, remote/rural, low HDI and WGI
2	High	Low-Moderate	Low-Moderate	Moderate and decreasing suitability, moderate production area
3	High	Moderate	Low	High but decreasing suitability, high population density, moderate production area
4	Low	High	Low	Very high suitabilty, no change in suitability, high-altitude, high population density, high production area, peri-urban
Sweetpotato				
1	Low	Low	High	High suitability, no change in suitability, remote/rural, low HDI and WGI
2	Moderate	Moderate	Moderate	Low-moderate and increasing suitability
3	Low	Moderate	Moderate	High suitability, no change in suitability, rural
4	Low	Moderate	Low	High suitability, no change in suitability, peri-urban

new varieties in this SAH. For potato, SAH 2 includes relatively remote areas with a lower population density, a higher travel time to urban areas, and a lower HDI compared to SAH 3. A shift to heat-tolerant varieties may be a low-cost option that is viable for farmers in both SAHs, but establishing an effective seed system to disseminate new heat-tolerant potato varieties may be more challenging in SAH 2 compared to SAH 3. Farmers in this SAH may need intensive extension support including demonstrations to be empowered to change their practices. Intercropping as an alternative to monocropping potato may be unattractive for farmers in SAH 3 because of land scarcity and potentially a high pull from the market for potato, and institutional innovations such as payment for environmental services and/or market demand creation for legume intercrops may be taken on board to stimulate uptake (Table 6). The assumptions on potential barriers to and drivers of adoption presented in Table 6 should be validated under real conditions, before being put in action to design scaling strategies.

4. Discussion

4.1. A spatial prioritisation framework based on an integrated assessment of risk

Crop suitability modelling has been used to assess spatially explicit impacts of climate change on different crops (Hyman et al., 2013; Jarvis et al., 2012; Manners et al., 2021; Manners et al., 2020; Manners and van Etten, 2018), but translating such data into tangible recommendations on adaptation strategies remains a challenge. Manners et al. (2021) modelled projected changes in suitability of the African GLR for RT&B crops, finding that although average changes in suitability will be positive for most crops except for potato, impacts were highly variable across the region.

We developed and presented a spatial prioritisation framework that explicitly integrates modelled impacts of climate change, the driving factors of that impact, and other indicators of climate-induced risk to cluster homologous regions in terms of the risk of climate-related impacts, so-called socio-agroecological homologues (SAHs). We illustrated how this framework can be used to inform *where* investments in R&D towards climate change adaptation are most needed, *what* kind of adaptation options address the most stringent climate change related stresses, and *how* enabling conditions for the uptake of these adaptation options can be created.

Climate-smart planning and strategy development should not only look at needs for adaptation driven by anticipated climate change impacts on biophysical systems, but move towards more holistic approaches considerate of socio-economic contexts and the capacity of individuals, communities and regions to adapt (IPCC, 2014; Manners and van Etten, 2018). This is supported by existing societal adaptation literatures where it is argued that the impacts of climate change on agriculture will not be solely driven by climate-related hazards, but by the interaction of hazards, exposure, and vulnerability including the adaptive capacity of societies affected (e.g. Castells-Quintana et al., 2018). Also, the capacity of farmers to manage the risk of climate-related impacts can be influenced by potential barriers to adoption of adapted climate-smart practices, evolving from constraints such as lack of capital, poor access to inputs, agricultural services and markets, and lack of labour (Notenbaert et al., 2017). The framework presented in this study allows for consideration of such barriers through taking the socio-economic characteristics of prioritised SAHs into account while developing context-specific scaling strategies.

4.2. Prioritising investments in CSA for RT&B crops in the GLR

The RT&B crops included in this study are deeply embedded in farming systems and food cultures in the Great Lakes Region, with around 50% of the daily caloric intake derived from these crops (Thiele and Friedmann, 2020). Average yields of RT&B crops across the region

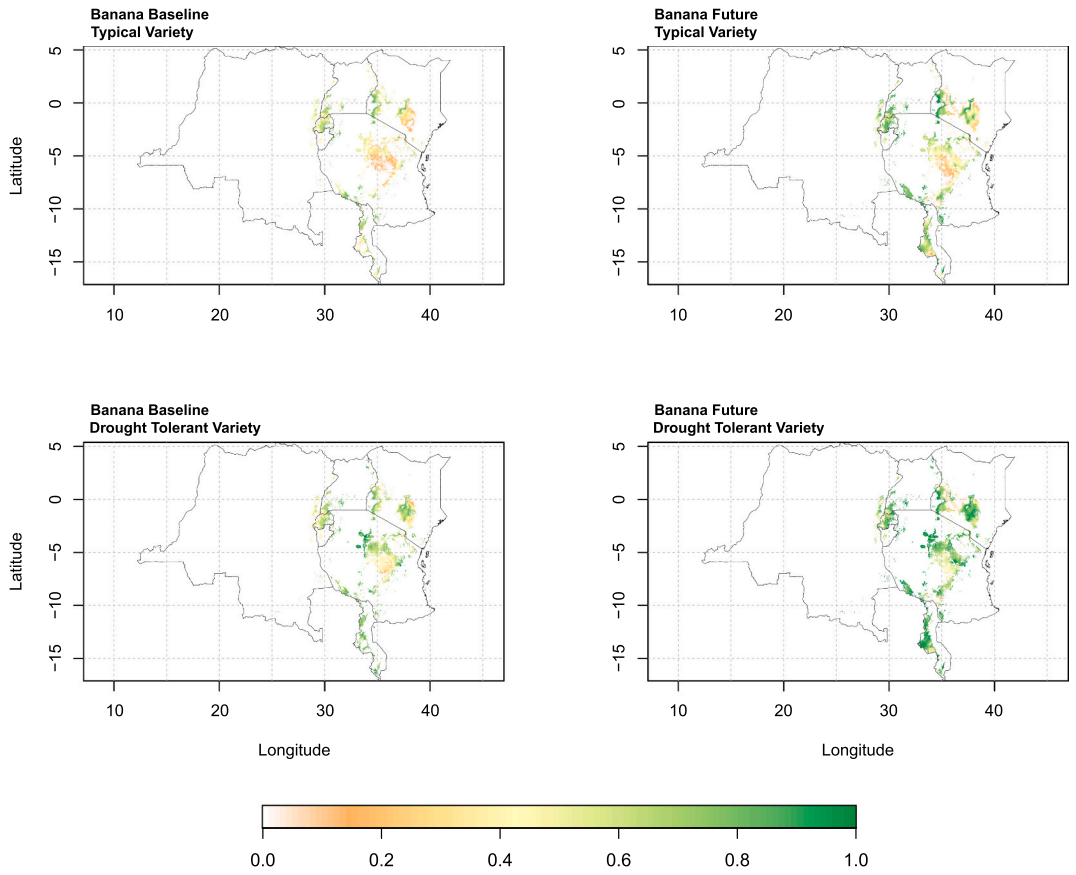

Fig. 3. Suitability for banana in SAH 2 under baseline (left) and future (right) climates, using typical (above) or drought-tolerant (below) varieties.

are below 10 t ha^{-1} (FAOSTAT, 2021), far below attainable yields. The low productivity levels are the result of a variety of factors, including lack of investment in healthy planting material of higher yielding varieties, poor crop management and unreliable weather conditions. The importance of RT&B crops in cultures and food security in the region partly results from the relatively favourable agroecological conditions for these crops compared to other staple crops such as cereals. Given the prominent role of these staple crops in farmer's livelihoods, efforts are made to commercialize value chains (e.g. through post-harvest innovation) as an avenue towards intensifying cropping systems and improving food security and incomes (Thiele et al., 2021). For this approach to be successful, environmental limitations resulting from climate-induced hazards, their spatial variation and temporal trends therein need to be well understood and addressed.

Although suitability for banana, cassava and sweetpotato will remain unchanged or increase under future climates in all SAHs, we identified SAHs with considerable production areas of each of the crops that are characterised by relatively low suitability under baseline and/or future climates. Scenario analysis pointed out that technologies and practices that increase resilience to drought, such as drought-tolerant varieties and practices that conserve soil moisture, can lift crop suitability to moderate or high levels in those SAHs. For potato, the framework allowed identifying clusters of geographies where negative impacts of climate change and the risks associated with that impact will be most severe. The framework also enabled characterization of innovations that can be targeted to those geographies to compensate the negative impacts.

It is important to note that the crop suitability model adopted for this study returns suitability values after determining the planting month that is associated with the highest crop suitability within the year (Manners et al., 2021). Hence, the model assumes that farmers will plant at the most ideal time during the year, and that farmers will adapt their planting schedules if ideal planting periods change over time. This is important for SAHs where suitability will be favoured under climate change, and where seemingly no interventions are needed. Farmers in such SAHs may need decision-support on planting time if those changes occur rapidly. Changes in ideal month for planting between baseline and future climates in the GLR are considerable as demonstrated by Manners et al. (2021).

4.3. Potential applications and users of the prioritisation framework

The framework allows for planning both short- and long-term interventions. In the short term, existing innovations can be targeted and validated in prioritised SAHs. In the long term, the framework can inform adaptive research agendas to develop new innovations responding to the future limiting factors in prioritised SAHs.

The tool can assist donors and policy makers to prioritise investments towards more exposed and vulnerable agricultural systems and populations and more impactful interventions that address proven climate-related constraints. It could be instrumental to engage decision makers in developing data-driven, climate-responsive plans, facilitated through science-policy dialogues (Zougmoré et al., 2019). Breeders at various levels (national, international) can use the framework to identify priority traits for breeding climate-resilient varieties and targeting of existing climate-resilient germplasm. As the development of new cultivars typically is a long-term process, providing breeders with this information will assist them in defensive breeding, aiming at cultivars that are adapted to the climate farmers will face 30–50 years from now (Hyman et al., 2013). Similarly, the framework can be used by agronomists to determine the type of climate-smart practices that are needed, now and in the future, to adapt to climate-induced risks. More generally, its outputs can inform processes of high-level, regional research agenda setting, in large scale operations such as the on-going integration of

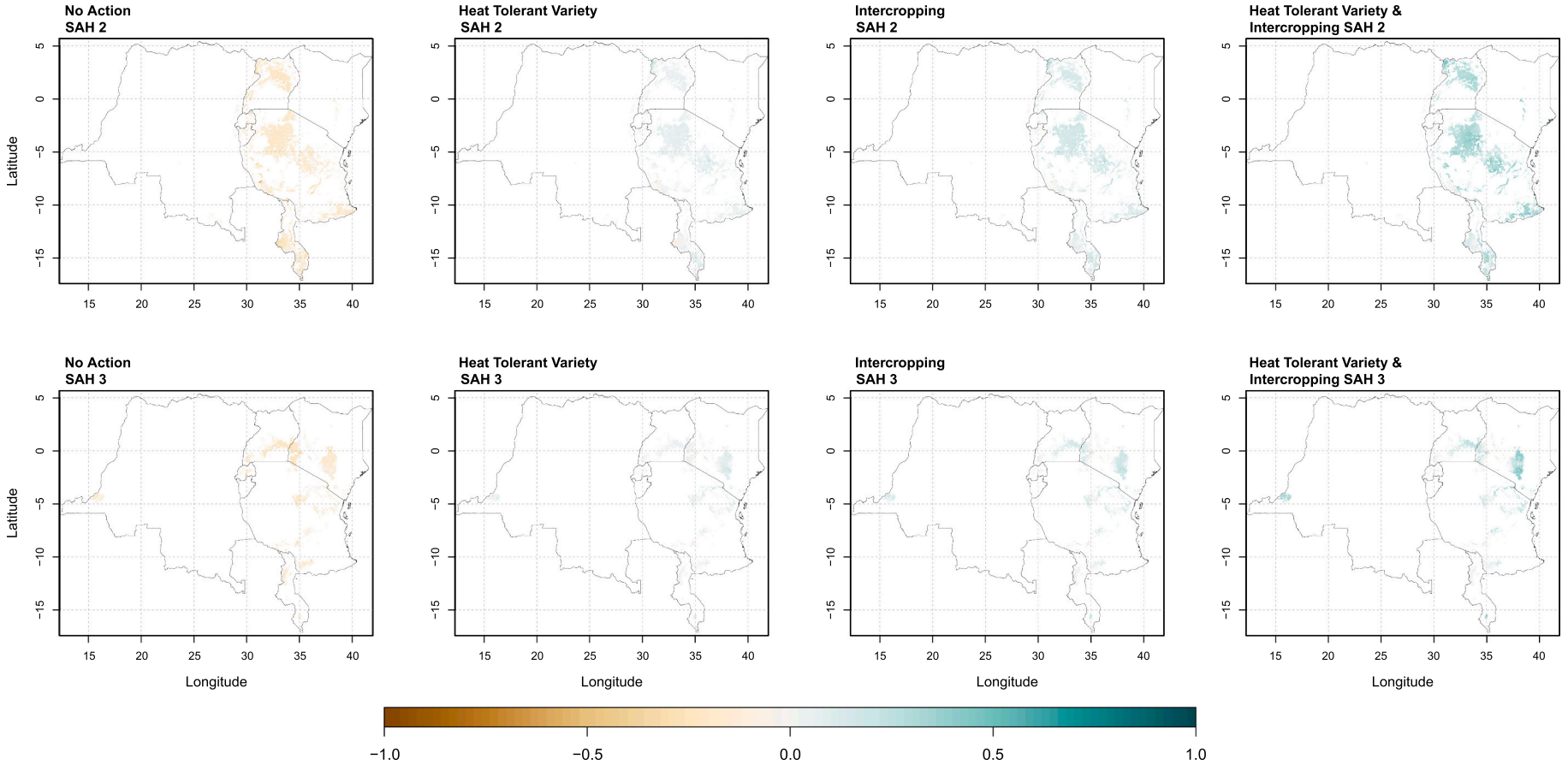

Fig. 4. Change in suitability for potato under future climates for two prioritised socio-agroecological homologues (SAH 2 and SAH 3) under four scenarios: (i) no action towards adaptation, (ii) introduction of heat-tolerant varieties, (ii) intercropping potato with legumes and (iv), heat-tolerant varieties intercropped with legumes.

Table 6
Examples of how the socio-economic characteristics of SAHs can help identify potential barriers to adoption, and inform scaling strategies.

SAH	Scenario/ adaptation option	Potential determinants of uptake	Examples of relevant scaling strategy components
Banana SAH 2	• Drought-tolerant varieties • Mulching	• Medium land sizes, labour availability • Moderate market access • Reasonable financial and human capacity to innovate	• Seed system based on decentralized seed multiplication • Promotion campaigns by local authorities
Potato SAH 2	• Heat-tolerant varieties • Intercropping with legumes	• Relatively remote and poor access to markets • Moderate land sizes and labour availability • Low financial and human capacity to innovate	• Seed system based on decentralized seed multiplication • Aggregation and market demand creation • Investment in capacity building of local extension agents • Farmer field schools (training, demonstrations,...)
Potato SAH 3		• Good access to markets • Small land sizes and low labour availability • High financial and human capacity to innovate	• Payments for environmental services • Market demand creation for legume crops • Promotion by radio, videos

CGIAR's capabilities, knowledge, assets, people, and global presence into One CGIAR (CGIAR System Organization, 2021). An important modality to deliver the One CGIAR's portfolio will be a set of Regional Integrated Initiatives, formulated to address specific priority regional challenges, each with a strong climate focus (CGIAR System Organization, 2021). Identifying, locating and describing driving factors in relation to climate risks in these regions will be a key step of interest to allocate resources strategically to R&D interventions that will have the greatest positive impact on agricultural systems under the threats posed by climate change.

The framework is a first step in the process of identifying *where* to work and on *what* and *how*, but could be extended to identify with *whom* to work to further increase the impact of agricultural R&D interventions. Recognition that farmers have different asset bases, kinship networks, and aspirations (Steiner et al., 2020; Thornton et al., 2018) is necessary to formulate relevant and context-specific interventions. Previous studies have considered the heterogeneity of farms in ex-ante assessments (Andrade et al., 2019; Claessens et al., 2012). To provide actionable outputs at this level of granularity (household) would require an informed understanding of the diversity of farming households within any landscape. This is inherently difficult, with geographically adjacent households found to be different across socio-economic and agronomic metrics (e.g. Hammond et al., 2020). A wealth of literature demonstrates that clustering of household types within homogeneous geographies is a viable solution (Cortez-Arriola et al., 2015; Hammond et al., 2020; Kuivanen et al., 2016; Tittonell et al., 2010). Combining information derived from the spatial prioritisation framework with farm typologies may provide a pathway for developing and scaling relevant, farm-type specific intervention packages (Steiner et al., 2020).

We illustrated the potential of the framework through a proof-of-concept application for a specific case study (RT&B crops in the Great Lakes Region) using a selection of eight indicators relevant to that case study. However, the framework was developed with the aim of being flexible enough to add, remove, or update indicators, relative to the specific objective of the user and the context of future applications, which may involve other geographies, farming systems and crops. The indicators for hazard, exposure and vulnerability used in this study are not exhaustive and other indicators can be selected for future iterations. This may involve the same indicators at a finer resolution (as they progressively become available), or entirely different indicators. Other crop or cropping system models can be used to derive indicators of climate-related hazards. Variables such as value of production per unit area or percentage of farm income for specific crops could be considered as indicators for exposure. Other potentially useful indicators for vulnerability include variables related to nutrition (e.g. percentage stunting) or availability of mobile networks and other ICTs.

In a next step, the relevance of the framework could be enhanced by engaging stakeholders in its design and application. We envision this is possible in three ways. First, stakeholders like policy makers, investors and farming communities themselves can be consulted for participatory indicator selection prior to applying the framework in a new context. Second, the same stakeholders can be engaged for participatory scenario development and design and testing of adaptation strategies. This could even involve farmer-led approaches, like the DEED cycle of Describe, Explain, Explore and Design to identify tailored options for adaptation (Descheemaeker et al., 2019; Giller et al., 2011). Participatory foresight methods can be used to engage farmers in exploring different scenarios to identify more desired, legitimate and effective scenarios (Van den Ende et al., 2021). Linking the spatial framework with farm typologies could facilitate the scalability of these rather intensive participatory approaches through providing a method for extrapolation. Third, we propose an iterative process of validation of the outputs of the prioritisation framework based on feedback loops from local and regional experts, as part of putting the framework in action.

Beyond agricultural R&D priority setting, we believe the flexibility of the analytical framework allows for applications in different contexts, such as the identification of future hotspots of conflict or insecurity in agricultural systems, stemming from climate change. There is a wealth of literature outlining the linkages between climatic changes affecting agriculture and conflicts and regional insecurity (Burke et al., 2009; World Food Programme, 2019). Therefore, with some modification in terms of indicators used, geographies with potentially similar propensity for conflict (based on similar socio-agroecological conditions including those related to climate risks) could be identified, prioritised, and specific policies developed to address the driving factors of risk before conflicts arise.

4.4. Limitations

The framework was limited by the availability of spatially-explicit socio-economic data. Great strides have been made in addressing these data gaps (e.g. Smits and Permanyer, 2019), but the availability of spatially-explicit socio-economic data lag, understandably, behind that of biophysical and climatic data. As new datasets come online, updated iterations of the framework could include them to provide a more resolved picture of climate impact risks and potential resilience. We used current, rather than projected, socio-economic data, because adaptation to climate change is a gradual process and we therefore assumed that socio-economic conditions of the present are more indicative of the capacity to adapt than those of the future. There are limitations to this assumption as socio-economic variables may rapidly change, especially under the influence of fast changing events and shocks like conflicts, the COVID-19 pandemic or climate tipping points. Outputs of the framework should therefore be continuously updated over time.

The modelling approach to determine environmental suitability for crops (EcoCrop) has some limitations including a lack of consideration of extreme weather events or variation in evapotranspiration, no

quantification of yield impacts, and no consideration of climate induced pest and disease impacts (see Manners et al., 2021; Ramirez-Villegas et al., 2013). Although the EcoCrop model also has major advantages (Manners et al., 2021), the prioritisation framework presented in this study allows to incorporate the outputs of more advanced modelling techniques once they become available for RT&B (and other under researched) crops. Advances are being made in using more robust mechanistic crop growth models to simulate the effects of climate change, also incorporating cultivar variations and other scenarios (Kleinwechter et al., 2016; Raymundo et al., 2017).

4.5. Next steps

We see the use of the framework as an iterative process that should involve feedback loops from validation with local and regional experts. In a next step, we will validate the outputs and recommendations generated by the framework with various types of experts such as decision-makers, breeders, agronomists and farmer organisations. Depending on the anticipated users, different types of user-friendly interfaces, ranging from interactive dashboards to paper-based visualizations, will be developed to facilitate the validation and use of the framework by different actors.

We are currently working on developing spatially-explicit data on pest and disease intensity and severity under baseline and future climates, and these will be incorporated in a next version of the framework. We will also look to source and include more resolved data on governance and human development indicators, to improve the understanding of variation in vulnerability to climate change impacts.

The indicators of hazard considered in this study were crop-specific, which allowed to consider crop-specific climate change impacts and prioritise actionable adaptation strategies. We acknowledge that smallholder farmers manage a variety of crops and livestock and that simultaneously considering climate change impacts on different components of cropping and farming systems could provide a more holistic picture of the risks smallholder farmers are facing. In a next step, the framework can be expanded to other major crops like cereals, and the analysis can combine indicators of hazards for the key crops of the farming systems of interest. Combining the analysis across different crops will also allow to generate recommendations on the potential of crop area expansion or crop switching. Combined data on decreases in suitability for some and increases in suitability for other crops in prioritised homologues may inform such strategies. For future applications, the framework could even be expanded to include both crop and livestock suitability, building on existing livestock suitability approaches (e.g. Thornton et al., 2021) allowing to analyse trade-offs and synergies in a whole-farm context.

5. Conclusion

We developed a spatial prioritisation framework based on delineating clusters of geographies with similar risks of climate-related impact as determined by the interaction between hazards, exposure and vulnerability. The framework was applied to RT&B crops in the African GLR as a proof-of-concept for how it can be used to formulate crop-specific recommendations for climate change adaptation. The methodology is flexible, replicable, and easily adaptable to other contexts, crops and locations. The cross-border SAHs reinforce the benefits of regional, rather than national, research and investment planning to address baseline and future climate impacts. The framework demonstrates the potential of aggregating multi-domain information for generating insights on how farming systems and people across geographies should be supported differently to adapt to future climates. We envisage the tool to be useful to a variety of R&D actors to identify priority geographical areas for climate action and for data-driven design of adaptation strategies to address climate risks in these areas.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

We would like to thank James Legg and Bernard Vanlauwe for providing useful comments to earlier versions of the manuscript. This research was undertaken as part of, and funded jointly by, the CGIAR Research Program on Roots, Tubers and Bananas (RTB) and the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS), which are both carried out with support from the CGIAR Trust Fund. For details, please visit https://www.cgiar.org/funders/ and https://ccafs.cgiar.org/donors. Additional funding support for this work was provided by the Belgian Directorate General for Development Cooperation and Humanitarian Aid (DGDC) through the Consortium for Improving Agricultural Livelihoods in Central Africa (CIALCA – www.cialca.org). The views expressed in this document cannot be taken to reflect the official opinions of all these funding organisations.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2022.103464.

References

Andrade, J.F., Rattalino Edreira, J.I., Farrow, A., van Loon, M.P., Craufurd, P.Q., Rurinda, J., Zingore, S., Chamberlin, J., Claessens, L., Adewopo, J., van Ittersum, M. K., Cassman, K.G., Grassini, P., 2019. A spatial framework for ex-ante impact assessment of agricultural technologies. Glob. Food Sec. 20, 72–81. https://doi.org/10.1016/j.gfs.2018.12.006.

Burke, M.B., Miguel, E., Satyanath, S., Dykema, J.A., Lobell, D.B., 2009. Warming increases the risk of civil war in Africa. Proc. Natl. Acad. Sci. U. S. A. 106, 20670–20674. https://doi.org/10.1073/pnas.0907998106.

Castells-Quintana, D., del Lopez-Uribe, M.P., McDermott, T.K.J., 2018. Adaptation to climate change: a review through a development economics lens. World Dev. 104, 183–196. https://doi.org/10.1016/j.worlddev.2017.11.016.

CGIAR System Organization, 2021. CGIAR 2030 Research and Innovation Strategy: Transforming Food, Land, and Water Systems in a Climate Crisis. CGIAR Systems Organization, Montpellier, France.

Charrad, M., Ghazzali, N., Boiteau, V., Niknafs, A., 2014. Nbclust: an R package for determining the relevant number of clusters in a data set. J. Stat. Softw. 61, 1–36. https://doi.org/10.18637/jss.v061.i06.

CIESIN, 2017. Gridded Population of the World, Version 4 (GPWv4): Population Density, Revision 10. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC) [WWW Document]. Columbia Univ. https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-rev1.

Claessens, L., Antle, J.M., Stoorvogel, J.J., Valdivia, R.O., Thornton, P.K., Herrero, M., 2012. A method for evaluating climate change adaptation strategies for small-scale farmers using survey, experimental and modeled data. Agric. Syst. 111, 85–95. https://doi.org/10.1016/j.agsy.2012.05.003.

Corbeels, M., de Graaff, J., Ndah, T.H., Penot, E., Baudron, F., Naudin, K., Andrieu, N., Chirat, G., Schuler, J., Nyagumbo, I., Rusinamhodzi, L., Traore, K., Mzoba, H.D., Adolwa, I.S., 2014. Understanding the impact and adoption of conservation agriculture in Africa: a multi-scale analysis. Agric. Ecosyst. Environ. 187, 155–170. https://doi.org/10.1016/j.agee.2013.10.011.

Cortez-Arriola, J., Rossing, W.A.H., Massiotti, R.D.A., Scholberg, J.M.S., Groot, J.C.J., Tittonell, P., 2015. Leverages for on-farm innovation from farm typologies? An illustration for family-based dairy farms in north-west Michoacán, Mexico. Agric. Syst. 135, 66–76. https://doi.org/10.1016/j.agsy.2014.12.005.

Crespo-Herrera, L.A., Crossa, J., Huerta-Espino, J., Mondal, S., Velu, G., Juliana, P., Vargas, M., Pérez-Rodríguez, P., Joshi, A.K., Braun, H.J., Singh, R.P., 2021. Target population of environments for wheat breeding in India: definition, prediction and genetic gains. Front. Plant Sci. 12, 1–15. https://doi.org/10.3389/fpls.2021.638520.

Descheemaeker, K., Ronner, E., Ollenburger, M., Franke, A.C., Klapwijk, C.J., Falconnier, G.N., Wichern, J., Giller, K.E., 2019. Which options fit best? Operationalizing the socio-ecological niche concept. Exp. Agric. 55, 169–190. https://doi.org/10.1017/S001447971600048X.

FAOSTAT, 2021. www.fao.org. Accessed 10 November 2021.

Fick, S.E., Hijmans, R.J., 2017. WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. Int. J. Climatol. 37, 4302–4315. https://doi.org/10.1002/joc.5086.

Giller, K.E., Tittonell, P., Rufino, M.C., van Wijk, M.T., Zingore, S., Mapfumo, P., Adjei-Nsiah, S., Herrero, M., Chikowo, R., Corbeels, M., Rowe, E.C., Baijukya, F.,

Mwijage, A., Smith, J., Yeboah, E., van der Burg, W.J., Sanogo, O.M., Misiko, M., de Ridder, N., Karanja, S., Kaizzi, C., K'ungu, J., Mwale, M., Nwaga, D., Pacini, C., Vanlauwe, B., 2011. Communicating complexity: integrated assessment of trade-offs concerning soil fertility management within African farming systems to support innovation and development. Agric. Syst. 104, 191–203. https://doi.org/10.1016/j.agsy.2010.07.002.

Hammond, J., Rosenblum, N., Breseman, D., Gorman, L., Manners, R., van Wijk, M.T., Sibomana, M., Remans, R., Vanlauwe, B., Schut, M., 2020. Towards actionable farm typologies: scaling adoption of agricultural inputs in Rwanda. Agric. Syst. 183, 102857 https://doi.org/10.1016/j.agsy.2020.102857.

Harrell, F., 2020. Hmisc [WWW Document]. https://cran.r-project.org/web/packages/Hmisc/index.html (accessed 3.25.20).

Hartkamp, A.D., White, J., Rodríguez, A., Banziger, M., Crossa, J., 2000. Maize Production Environments Revisited: A GIS-Based Approach. CIMMYT, Mexico.

Hijmans, R.J., 2021. raster: Geographic Data Analysis and Modeling. R package version 3.4-13 [WWW Document]. https://cran.r-project.org/package=raster.

Hyman, G., Hodson, D., Jones, P., 2013. Spatial analysis to support geographic targeting of genotypes to environments. Front. Physiol. 1–14. https://doi.org/10.3389/fphys.2013.00040, 4 MAR.

IFPRI, 2019. Global Spatially-Disaggregated Crop Production Statistics Data for 2010 Version 2.0 [WWW Document]. https://doi.org/10.7910/DVN/PRFF8V.

IPCC, 2014. Summary for policymakers. In: Field, C.B., Barros, V.R., Dokken, D.J., Mach, K.J., Mastrandrea, M.D., Bilir, T.E., Chatterjee, M., Ebi, K.L., Estrada, Y.O., Genova, R.C., Girma, B., Kissel, E.S., Levy, A.N., MacCracken, S., Mastrandrea, P.R., White, L.L. (Eds.), Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY.

Jarvis, A., Ramirez-Villegas, J., Campo, B.V.H., Navarro-Racines, C., 2012. Is cassava the answer to African climate change adaptation? Trop. Plant Biol. 5, 9–29. https://doi.org/10.1007/s12042-012-9096-7.

Kaufman, L., Rousseeuw, P.J., 1990. Finding Groups in Data: An Introduction to Cluster Analysis. John Wiley & Sons, Inc. https://doi.org/10.1002/9780470316801.

Kleinwechter, U., Gastelo, M., Ritchie, J., Nelson, G., Asseng, S., 2016. Simulating cultivar variations in potato yields for contrasting environments. Agric. Syst. 145, 51–63. https://doi.org/10.1016/j.agsy.2016.02.011.

Kuivanen, K.S., Alvarez, S., Michalscheck, M., Adjei-Nsiah, S., Descheemaeker, K., Mellon-Bedi, S., Groot, J.C.J., 2016. Characterising the diversity of smallholder farming systems and their constraints and opportunities for innovation: a case study from the northern region, Ghana. NJAS - Wageningen J. Life Sci. 78, 153–166. https://doi.org/10.1016/j.njas.2016.04.003.

Lemessa, S.D., Yismaw, M.A., Watabaji, M.D., 2019. Risk induced farmers' participation in agricultural innovations: evidence from a field experiment in eastern Ethiopia. Dev. Stud. Res. 6, 106–117. https://doi.org/10.1080/21665095.2019.1629323.

Maechler, M., Rousseeuw, P., Struyf, A., Hubert, M., Hornik, K., 2021. cluster: Cluster Analysis Basics and Extensions. R package version 2.1.2. [WWW Document]. https://cran.r-project.org/web/packages/cluster/.

Manners, R., van Etten, J., 2018. Are agricultural researchers working on the right crops to enable food and nutrition security under future climates? Glob. Environ. Chang. 53, 182–194. https://doi.org/10.1016/j.gloenvcha.2018.09.010.

Manners, R., Varela-Ortega, C., van Etten, J., 2020. Protein-rich legume and pseudo-cereal crop suitability under present and future European climates. Eur. J. Agron. 113, 125974 https://doi.org/10.1016/j.eja.2019.125974.

Manners, R., Vandamme, E., Adewopo, J., Thornton, P., Friedmann, M., Carpentier, S., Ezui, K.S., Thiele, G., 2021. Crop suitability of root, tuber, and banana crops in Central Africa may be favoured under future climates through location-specific shifts to different variety types. Agric. Syst. 193, 103246.

Mubiru, D.N., Radeny, M., Kyazze, F.B., Zziwa, A., Lwasa, J., Kinyangi, J., Mungai, C., 2018. Climate trends, risks and coping strategies in smallholder farming systems in Uganda. Clim. Risk Manag. 22, 4–21. https://doi.org/10.1016/j.crm.2018.08.004.

Muthoni, F.K., Zhe, G., Bekunda, M., Sseguya, H., Kizito, F., Baijukya, F., Hoeschle-Zeledon, I., 2017. Sustainable recommendation domains for scaling agricultural technologies in Tanzania. Land Use Policy 66, 34–48. https://doi.org/10.1016/j.landusepol.2017.04.028.

Notenbaert, A., Herrero, M., De Groote, H., You, L., Gonzalez-Estrada, E., Blummel, M., 2013. Identifying recommendation domains for targeting dual-purpose maize-based interventions in crop-livestock systems in East Africa. Land Use Policy 30, 834–846. https://doi.org/10.1016/j.landusepol.2012.06.016.

Notenbaert, A., Pfeifer, C., Silvestri, S., Herrero, M., 2017. Targeting, out-scaling and prioritising climate-smart interventions in agricultural systems: lessons from applying a generic framework to the livestock sector in sub-Saharan Africa. Agric. Syst. 151, 153–162. https://doi.org/10.1016/j.agsy.2016.05.017.

Nyawade, S.O., Karanja, N.N., Gachene, C.K.K., Gitari, H.I., Schulte-Geldermann, E., Parker, M.L., 2019. Intercropping optimizes soil temperature and increases crop water productivity and radiation use efficiency of Rainfed potato. Am. J. Potato Res. 96, 457–471. https://doi.org/10.1007/s12230-019-09737-4.

Omamo, S.W., Diao, X., Wood, S., Chamberlin, J., You, L., Benin, S., Wood-Sichra, U., Tatwangire, A., 2006. Strategic Priorities for Agricultural Development in Eastern and Central Africa. Washington. https://doi.org/10.2499/9780896291584RR150.

Petsakos, A., Prager, S.D., Gonzalez, C.E., Gama, A.C., Sulser, T.B., Gbegbelegbe, S., Kikulwe, E.M., Hareau, G., 2019. Understanding the consequences of changes in the production frontiers for roots, tubers and bananas. Glob. Food Sec. 20, 180–188. https://doi.org/10.1016/j.gfs.2018.12.005.

Rajaram, S., van Ginkel, M., Fischer, R.A., 1994. CIMMYT's wheat breeding mega-environments (ME). In: Li, Z.S., Xin, Z.Y. (Eds.), Proceedings of the 8th International Wheat Genetics Symposium. Chinese Academy of Agricultural Sciences, Beijing, China (pp. 1101-11–6).

Ramirez, J., Jarvis, A., 2010. Downscaling Global Circulation Model Outputs: The delta Method. Decision and Policy Analysis Working Paper No. 1. Decision and Policy Analysis, Cali, Colombia.

Ramirez-Villegas, J., Jarvis, A., Läderach, P., 2013. Empirical approaches for assessing impacts of climate change on agriculture: the EcoCrop model and a case study with grain sorghum. Agric. For. Meteorol. 170, 67–78. https://doi.org/10.1016/j.agrformet.2011.09.005.

Rattalino Edreira, J.I., Cassman, K.G., Hochman, Z., Van Ittersum, M.K., Van Bussel, L., Claessens, L., Grassini, P., 2018. Beyond the plot: technology extrapolation domains for scaling out agronomic science. Environ. Res. Lett. 13 https://doi.org/10.1088/1748-9326/aac092.

Raymundo, R., Asseng, S., Prassad, R., Kleinwechter, U., Concha, J., Condori, B., Bowen, W., Wolf, J., Olesen, J.E., Dong, Q., Zotarelli, L., Gastelo, M., Alva, A., Travasso, M., Quiroz, R., Arora, V., Graham, W., Porter, C., 2017. Performance of the SUBSTOR-potato model across contrasting growing conditions. F. Crop. Res. 202, 57–76. https://doi.org/10.1016/j.fcr.2016.04.012.

Salau, O.A., Opara-Nadi, O.A., Swennen, R., 1992. Effects of mulching on soil properties, growth and yield of plantain on a tropical ultisol in southeastern Nigeria. Soil Tillage Res. 23, 73–93. https://doi.org/10.1016/0167-1987(92)90006-W.

Shiferaw, B.A., Okello, J., Reddy, R.V., 2009. Adoption and adaptation of natural resource management innovations in smallholder agriculture: reflections on key lessons and best practices. Environ. Dev. Sustain. 11, 601–619. https://doi.org/10.1007/s10668-007-9132-1.

Smits, J., Permanyer, I., 2019. The subnational human development database. Sci. Data 6, 190038.

Steiner, A., Aguilar, G., Bomba, K., Bonilla, J., Campbell, A., Echeverria, R., Gandhi, R., Hedegaard, C., Holdorf, D., Ishii, N., Quinn, K., Ruter, B., Sunga, I., Sukhdev, P., Verghese, S., Voegele, J., Winters, P., Campbell, B., Dinesh, D., Huyer, S., Jarvis, A., Loboguerrero Rodriguez, A.M., Millan, A., Thornton, P., Wollenberg, L., Zebiak, S., 2020. Actions to Transform e Food Systems under Climate Change. Wageningen, The Netherlands.

Thiele, G., Friedmann, M., 2020. Research Brief 02. The vital importance of RTB crops in the One CGIAR portfolio. CGIAR Research Program on Roots, Tubers and Bananas, Lima, Peru.

Thiele, G., Dufour, D., Vernier, P., Mwanga, R.O.M., Monica, L., Gotor, E., Wossen, T., Geldermann, E.S., Kikulwe, E., Kouakou, A.M., Friedmann, M., Hershey, C., 2021. Review A review of varietal change in roots, tubers and bananas: consumer preferences and other drivers of adoption and implications for breeding. Int. J. Food Sci. Technol. 56, 1076–1092. https://doi.org/10.1111/ijfs.14684.

Thornton, P.K., Whitbread, A., Baedeker, T., Cairns, J., Claessens, L., Baethgen, W., Bunn, C., Friedmann, M., Giller, K.E., Herrero, M., Howden, M., Kilcline, K., Nangia, V., Ramirez-Villegas, J., Kumar, S., West, P.C., Keating, B., 2018. A framework for priority-setting in climate smart agriculture research. Agric. Syst. 167, 161–175. https://doi.org/10.1016/j.agsy.2018.09.009.

Thornton, P., Nelson, G., Mayberry, D., Herrero, M., 2021. Increases in extreme heat stress in domesticated livestock species during the twenty-first century. Glob. Chang. Biol. 27, 5762–5772. https://doi.org/10.1111/gcb.15825.

Tittonell, P., Muriuki, A., Shepherd, K.D., Mugendi, D., Kaizzi, K.C., Okeyo, J., Verchot, L., Coe, R., Vanlauwe, B., 2010. The diversity of rural livelihoods and their influence on soil fertility in agricultural systems of East Africa - a typology of smallholder farms. Agric. Syst. 103, 83–97. https://doi.org/10.1016/j.agsy.2009.10.001.

USGS, 2020. USGS EROS Archive - Digital Elevation - Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010) [WWW Document]. https://www.usgs.gov/centers/eros/science/usgs-eros-archive-digital-elevation-global-multi-resolution-terrain-elevation?qt-science_center_objects=0#qt-science_center_objects (accessed 11.15.20).

Van den Ende, M., Wardekker, A., Mees, H., Hegger, D., Vervoort, J., 2021. Towards a Climate-Resilient Future Together - a Toolbox with Participatory Foresight Methods, Tools and Examples from Climate and Food Governance. Utrecht University, Utrecht.

Weiss, D.J., Nelson, A., Gibson, H.S., Temperley, W., Peedell, S., Lieber, A., Hancher, M., Poyart, E., Belchior, S., Fullman, N., Mappin, B., Dalrymple, U., Rozier, J., Lucas, T.C.D., Howes, R.E., Tusting, L.S., Kang, S.Y., Cameron, E., Bisanzio, D., Battle, K.E., Bhatt, S., Gething, P.W., 2018. A global map of travel time to cities to assess inequalities in accessibility in 2015. Nature 553, 333–336. https://doi.org/10.1038/nature25181.

World Bank, 2019. Worldwide Governance Indicators [WWW Document]. https://info.worldbank.org/governance/wgi/.

World Food Programme, 2019. Climate Change and Conflict: Improving Prospects for Peace Through WFP Climate Action [WWW Document] (org/api/documents/WFP-0000108179/download/?_ga=2.4218358.417837866.1584107761-1697953616.1582556836).

Xiong, J., Thenkabail, P.S., Gumma, M.K., Teluguntla, P., Poehnelt, J., Congalton, R.G., Yadav, K., Thau, D., 2017. Automated cropland mapping of continental Africa using Google earth engine cloud computing. ISPRS J. Photogramm. Remote Sens. 126, 225–244. https://doi.org/10.1016/j.isprsjprs.2017.01.019.

Zougmoré, R.B., Partey, S.T., Totin, E., Ouédraogo, M., Thornton, P., Karbo, N., Sogoba, B., Dieye, B., Campbell, B.M., 2019. Science-policy interfaces for sustainable climate-smart agriculture uptake: lessons learnt from national science-policy dialogue platforms in West Africa. Int. J. Agric. Sustain. 17, 367–382. https://doi.org/10.1080/14735903.2019.1670934.