Vulnerability of crop yields to variations in growing season precipitation in Uganda

Terence Epule Epule^{1,2} · Mark George New¹

© Springer Nature Switzerland AG 2019

Abstract

This study aims at assessing the vulnerability of six key crops (maize, beans, cassava, millet, groundnuts, and sweet potatoes) to variations in growing season precipitation at both the national and regional scale (southwest) in Uganda. To achieve this objective, a vulnerability model that is a function of sensitivity, exposure and adaptive capacity is used. Crop yield data for the period 1998–2017 for both the national scale and regional level analysis were collected from FAOSTAT and the Crop Yield Gap Atlas respectively. Precipitation data for the period 1998–2017 for both the national scale and regional level analysis were collected from the Climate Change Knowledge Portal of the World Bank Group. Adaptive capacity which reflects how the crops and the farmers growing these crops are adapted was measured using two proxies (literacy and poverty rates) and were collected from the Uganda Bureau of Statistics, UBOS (Uganda national household survey 2002/2003, 2002. https://www.ubos.org/wp-content/uploads/publications/03_2018unhs_200203_report.t.PDF; 2002 Uganda population and household census analytical report: education and literacy, 2006. <http://www.ubos.org/onlinefiles/uploads/ubos/pdf%20documents/2002%20CensusEducAnalyticalReport.pdf>; Uganda national household survey 2012/2013, 2014. https://www.ubos.org/wp-content/uploads/publications/04_20182012_13_UNHS_Final_Report.pdf; Uganda national household survey 2016/2017, 2018. https://www.ubos.org/wp-content/uploads/publications/03_20182016_UNHS_FINAL_REPORT.pdf) and Daniels (Measuring poverty trends in Uganda with non-monetary indicators, 2011. http://www.fao.org/fileadmin/templates/ess/pages/rural/wye_city_group/2011/documents/session3/Daniels_-_Paper.pdf). The results show that at the national scale, cassava is the most vulnerable crop while maize is the least vulnerable crop while at the regional scale millet is the most vulnerable crop and sweet potatoes are least vulnerable. At both scales, vulnerability has a positive relationship with exposure and sensitivity and an inverse relationship with adaptive capacity. The coefficients of determination at both scales are equally above 50% for most of the indices indicating that the models presented here are generally reliable and can be explained by the linear relationship between the variables. This study underscores the importance of regionally focused studies being that national and more global studies often have results that diverge from regional trends due to internal variations in precipitation, temperature, poverty and literacy rates at different levels. Proposing adaptation options that will be applicable at the regional scale must require studies like this involving results from both regional and national scale analysis.

Keywords Vulnerability · Sensitivity · Exposure · Adaptive capacity · Precipitation · Drought · Literacy · Poverty · Uganda

Electronic supplementary material The online version of this article (<https://doi.org/10.1007/s42452-019-0912-7>) contains supplementary material, which is available to authorized users.

✉ Terence Epule Epule, terence.epule@uct.ac.za; terence.epule@mail.mcgill.ca | ¹African Climate and Development Initiative (ACDI), University of Cape Town, Upper Campus, Geological Sciences Building, Level 6, 13 Library Road, Rondebosch 7700, South Africa. ²Department of Geography, McGill University, 805 Burnside Hall, Montreal, QC H3A0B9, Canada.

SN Applied Sciences (2019) 1:899 | <https://doi.org/10.1007/s42452-019-0912-7>

Received: 25 February 2019 / Accepted: 11 July 2019 / Published online: 23 July 2019

1 Introduction

In the last three and a half decades, sub-Saharan Africa (SSA) has witnessed climate warming in the range of between 0.2 and 2.0 °C [53]; recent projections in the sixth assessment report (AR6) suggest future temperature variations of between 1.5 and 2.5 °C for the baseline and worse case scenarios respectively [50]. This increase is disturbing because agriculture which is the 'life wire' of most SSA countries is essentially rain-fed and is in the hands of small-scale peasant farmers who are poorly equipped to adequately respond to climate change through adaptation [9, 11, 29, 31, 32, 51, 74, 76, 78, 86, 97].

Previously, the fifth assessment report (AR5) of the IPCC showed that on a decadal basis, mean temperatures are likely to increase by 1.8 °C by 2020, by about 1.9 °C by 2030, by about 1.8 °C by 2040, by about 1.7 °C by 2050 and by about 1.2 °C by 2100 [52]. The early repercussions of these predictions are variations in temperature and precipitation and increase vulnerability of agricultural systems, increase poverty, low adaptive capacity and increase in climate stressors [20, 66, 67]. In spite of the importance of climate in the SSA region, non-climatic drivers such as agricultural expansion, deforestation, occasioned by rapid population growth have tilted the debate on which of climatic or non-climatic drivers are the stressors. Therefore, is therefore a current interest in global change research that is considering the role of significant non-climatic drivers in shaping development and environmental protection across SSA and Africa [43].

Globally, the influence of climatic variables on agricultural production systems is acknowledged. As such, climate change cannot be excluded from the environmental and development debates across Africa and in most parts of the world because the rate at which agrarian ecosystems will respond to climate change will determine the pace of African development [43, 44]. This current study is one effort geared towards obtaining a better understanding of the role of precipitation variations on agricultural systems. However, in Africa south of the Sahara a myriad of climatic and non-climatic variables are tilting the debate on what is driving the current trends in agricultural production [44].

To grapple with these climate change uncertainties, the use of integrative monitoring approaches that reflect several empirical indices and captures the role of climatic and non-climatic variables can help scientists assess the degree of vulnerability of cropping systems to climatic and non-climatic variables [14, 48, 65, 84, 91, 103]. Vulnerability has been previously assessed using several indices. Some examples include the Notre Dame Global

Adaptation Index (ND-GAIN) [12], the crop-drought indicator [92], water-poverty index [1, 25, 96], livelihood vulnerability index [46] and farmers vulnerability to global change index in the context of large-scale irrigation as maladaptation [2]. However, this current vulnerability index was developed specifically for application in an African crop farming context and it has as advantage its ability to use proxies to capture adaptive capacity in a continent where data availability is often a big issue.

The current vulnerability index was used because in addition to the fact that it is more suitable for studies in African contexts, it enables us to easily represent variables such as adaptive capacity which are generally difficult to estimate due to data deficiency in most African contexts [20, 21]. Despite these strengths, the current adaptive capacity index is limited in that it uses proxy indicators to represent adaptive capacity. Also, being that these indicators vary from one country to another, it is difficult to standardize the adaptive capacity part of the equation. In addition, a lack of information on the choice of appropriate variables and their relative weighting required to establish a value index in a region [63].

Increased understanding of the potential effects of climate change, climate variability and extreme events is important in planning adaptation and mitigation options [60]. These models can leverage the influence of historical data on crop yields as they have the advantage of limited reliance on field calibration data and are much more able to transparently assess the level of uncertainty of the model as reflected by their coefficients of determination. However, they are limited because of issues of co-linearity and stationarity [24, 45, 60, 102].

The six crops considered for this analysis play an important role in the diet and food charts of the average Ugandan and were selected for the following reasons: (1) they are among the most widely cultivated, affordable, and most widely grown crops in Uganda and Africa [9, 23, 62] (2) these crops constitute staple foods and play an income generation role as they are often transformed and sold (3) they are mainly grown (~90%) by small-scale peasant farmers [10, 18, 22, 58, 70, 73, 80] and (4) they grow across the country in different agro-climatic zones due to their higher tolerance range [70, 73]. Despite the importance above, gaps still exist in the context of the relationships that these crops have with precipitation in Uganda. For example, there are no studies that have analysed the vulnerability of these/several crops based on historical climate and crop yield data at both the national and regional scales in Uganda. The only studies that come close to the objectives of this current study were focused on how maize yields respond to droughts at the national scale and at five districts in the north and south of the country [20, 21]. Others have focused on precipitation deficits

and temperature changes, [68, 69] while [54, 55, 79] have employed the use of physical and social perspectives to assess the vulnerability of maize yields to droughts at the SSA level. As such, this paper assesses the vulnerability of six crops at two scales with an objective of verifying how vulnerability varies at different spatial scales in Uganda. This study is important because a better understanding of the vulnerability of these crops can help to inform adaptation options to better handle recurrent droughts. By understanding the crops that are less or more vulnerable, it becomes easier to identify adjustments that are required to support the less adaptive crops.

2 Study area

The agricultural sector in Uganda accounts for about 20% of Uganda's GDP, employs about 73% of the population, and contributes about 48% to export earnings [49, 57, 80]. It has been argued that poverty reduction in Uganda is inextricably tied to innovations in the agricultural sector [49]. There is increasing evidence of the effects of droughts on crops and crop prices in Uganda; for example, in 2008, 2009, 2010 and 2011 droughts compromised

hydroelectricity-power generation, livestock and food production and created a deficit of about 2.8 trillion (2.8×10^{12}) Uganda shillings; an equivalent of US\$ 1.2 billion ($US\$1.2 \times 10^9$); 7% of Uganda's GDP [17].

In 2013, Uganda an East African country had a population of about ~36 million [72]. Uganda has a humid equatorial climate with average annual precipitation ranging between 800 and 1500 mm. In the south of Uganda, precipitation is bi-modal being dominant from March–May and September–November. In the north of Uganda, precipitation is uni-modal, dominant from April–October [26, 41]. Temperature on its part varies minimally across the country, this study will base its analysis on precipitation which is a vital crop yield determinant in Uganda's crop production system [26, 70] (Fig. 1).

3 Methods

This paper employs explorations at two scales to enhance an assessment of how the vulnerability of these crops varies as one scales down from national to regional scale. This approach provides a baseline against which comparisons can be made and will go a long way in helping adaptation

Fig. 1 Map of Uganda showing the different regions

efforts in the agricultural sector. It is worth noting that a comparison of the regional or southwest scale findings with our exploration at a national scale helps to further situate the regional scale findings in the context of what obtains at the national scale. When southwest scale observations are higher/lower than national scale observations, the degree of intensity of vulnerability can be judged as either exceptionally high or exceptionally low relative to the national scale observations.

While our exploration at a national scale implies that the data covers all the growing seasons for each of the crops for the entire country spanning north to south and east to west; the regional matrix is the southwest of the country. This region was selected because it is an important thematic zone for the cultivation of the six crops above and is inhabited by populations that are essentially farmers and gatherers such as the Batwa pygmies whose livelihoods depend entirely on the land. In this paper, vulnerability is a function of sensitivity, exposure and adaptive capacity. The sections that follow will define these terminologies as well as the methods used in fitting the models.

3.1 Vulnerability

Vulnerability is defined as the extent to which a system is susceptible or exposed to and unable to cope with the negative effects of climate change, climate variability and extreme weather events [53, 89]. Vulnerability in the context of this paper assesses the ability of cropping systems to cope with multiple stressors and shocks including climate change and variability driven by cultural, political, and socio-economic drivers interacting with climate to render some households, communities, regions, countries, and continents more susceptible to climate change, climate variability and extreme events [92]. Consistent with the general vulnerability scholarship [9, 29, 38, 41, 64, 77, 90] vulnerability is driven by: (1). the *sensitivity* [29, 30], (2). the level of *exposure* [29, 30] and (3) the *adaptive capacity* which is the ability of the crops and farmers to absorb the stress caused by variations in elements of climate such as precipitation measured in this study through proxies of adaptive capacity such as literacy and poverty rates [19, 29, 33, 34, 70, 75, 94]. The vulnerability index proposed here is based on a sub-index for each of the above components of vulnerability to assess the degree of vulnerability of the six crops to droughts at the national and southwestern scales in Uganda. To fit the empirical crop models, this paper uses a composite vulnerability index (Eq. 1) which builds on builds other vulnerability indices such as the Notre Dame Global Adaptation Index (ND-GAIN) [12], the crop-drought indicator [92], and the water-poverty index [1, 25, 96] but this current index is unique in that it is developed specifically for application

in an African crop farming context. It is important to note that the vulnerability index used here combines crop yield and precipitation data in the context of the sensitivity and exposure indices respectively while the adaptive capacity index uses proxies of adaptive capacity that are relevant to Uganda such as literacy and poverty rates. Therefore, the vulnerability index captures crop specific parameters such as yield and precipitation and characteristics of the farmers that enhance or reduce adaptive capacity as proxies. A summary of the indices used, and their components are represented on Table 1.

$$VU_{xi} = SE_{xi} + EX_{xi} - ADC_{xi} \quad (1)$$

where VU_{xi} is the crop yield (beans, maize, cassava, groundnuts, millet and sweet potatoes) vulnerability index, SE_{xi} is the crop yield sensitivity index, EX_{xi} is the crop yield exposure index and ADC_{xi} is the crop yield adaptive capacity index.

3.2 Sensitivity index

The sensitivity index describes the quantifiable decline in crops yields due to climate change, climate variations and extreme events [29, 30, 53, 89]. It can also be described as the manifestations of climate change, climate variability and extreme events in a cropping system. For the regional scale (southwest Uganda) analysis, time series data for the period 1998 to 2017 on actual crop yields (tons/ha/year) for all the six crops under investigation were collected from the Global Yield Gap Atlas [56, 57]. At the national scale, time series data from 1998 to 2017 on actual crop yields (hectograms/ha/year converted to tons/ha/year) were collected from FAOSTAT [27]. These time scales were selected because of the availability of data. The actual crop yield data for the regional as well as national scale analysis were subjected to detrending by removing a linear model in the time series by dividing the projected linear trend by the actual linear trend (Eq. 2). This exercise (detrending) removes the repercussions of increased technology, illustrates annual crop yield variations attributable to precipitation, reduces the effects of consistent reporting errors and results in our projected or expected crop yields [19, 59, 61]. The projected or expected crop yields were projected

Table 1 Summary of indices and their components

Indices	Components/model inputs
Vulnerability index	Sensitivity index, exposure index and adaptive capacity index
Sensitivity index	Actual & projected crop yields
Exposure index	Growing season precipitation
Adaptive capacity index	Proxies: poverty and literacy rates

for each year by using the trend line equation for a simple linear regression (Eq. 2). At both the nation and the regional scale, the actual crop yield data were regressed with the precipitation data. The sensitivity indices for the various crops at both the national and regional scale were fitted by dividing the mean expected crop yields by the mean actual maize yields (Eqs. 3, 4). This approach is like that used by Simelton et al. [92] and Antwi-Agyei et al. [5] in identifying the socio-economic indicators associated with sensitivity and resilience to droughts for each of Chi-na's main grain crops.

$$EXP_{ym} = ax + b \quad (2)$$

where EXP_{ym} is the expected crop yield at regional or national scale, x is the year, a is the linear trend, b is the intercept when $EXP_{ym} = ax$

$$SE_{xr} = \frac{EXP_{yr}}{ACT_{yr}} \quad (3)$$

where SE_{xr} is the crop yield sensitivity index at the regional scale, EXP_{yr} is the mean projected or expected crop yield at the regional scale, ACT_{yr} is the mean actual maize yield at the regional scale.

$$SE_{xn} = \frac{EXP_{yn}}{ACT_{yn}} \quad (4)$$

where SE_{xn} is the crop yield sensitivity index at the national scale, EXP_{yn} is the mean projected or expected crop yield at the national scale, ACT_{yn} is the mean actual maize yield at the national scale.

3.3 Exposure index

The exposure index describes the extent and nature of the stimulus reflected in the magnitude, intensity and duration of the drought [29, 30, 53, 89]. To fit this index, precipitation data for the period 1998–2017 were used to reflect the extent to which the crops were exposed to droughts. It is important to note that, for each crop only the growing season precipitation data were used to fit the model. Spatial variations in the growing season for the six crops exists in Uganda. The national scale analysis was based on the following crop calendars studies [28, 40, 85] while the regional scale analysis was based on a crop calendar obtained in the summer of 2018 through field work in parts of south west Uganda such as the Batwa pygmies' zone (Fig. 2).

To fit the model for the national scale analysis, the mean short- and long-term growing season precipitation time series data from 1998 to 2017 were obtained from the Climate Change Knowledge Portal of the World Bank

Group [104]. These data were validated by averaging over the crop growing months for each 5' × 5' grid for Uganda from the Global Crop Calendar Dataset [85]. At the regional scale the mean short and long term growing season precipitation from 1998 to 2017 were also culled from the Climate Change Knowledge Portal of the World Bank Group [104]. At both the nation and the regional scale, the mean growing season precipitation and annual growing season precipitation data were regressed against crop yield data for the period 1998–2017. The exposure index was now fitted by dividing the mean long-term crop growing season precipitation by the mean precipitation for each year during the crop growing season (Eqs. 5, 6). This is same as the procedures used in other studies [5, 35, 36, 92]. In fitting the exposure index models, only precipitation data were used because precipitation is the most vital agro-climatic variable in Uganda [93].

$$EX_{xir} = \frac{\mu LT_{cgs ppt(1998\ to\ 2017)}}{\mu STY_{cgs ppt(1998\ to\ 2017)}} \quad (5)$$

where EX_{xir} is the crop yield exposure index at the regional scale, $\mu LT_{cgs ppt(1998\ to\ 2017)}$ is the mean long term crop growing season precipitation from 1998 to 2017 for the regional scale analysis, $\mu STY_{cgs ppt(1998\ to\ 2017)}$ is the mean precipitation for each year's crop growing season from 1998 to 2017 at a regional scale.

$$EX_{xi_ns} = \frac{\mu LT_{cgs ppt(1998\ to\ 2017)}}{\mu STY_{cgs ppt(1998\ to\ 2017)}} \quad (6)$$

where EX_{xi_ns} is the crop yield exposure index at a national scale, $\mu LT_{cgs ppt(1998\ to\ 2017)}$ is the mean long term crop growing season precipitation from 1998 to 2017 at a national scale, $\mu STY_{cgs ppt(1998\ to\ 2017)}$ is the mean precipitation for each year's crop growing season from 1998 to 2017 at a national scale.

3.4 Adaptive capacity index

This is the ability of a production system to adjust/adapt or cope with multiple stressors and shocks including climate change, climate variability and extreme events [29, 30, 53]. The magnitude of the effects a drought has on crop yields is often determined by the adaptive capacity of the system to manage the drought reflected in proxies such as literacy and poverty rates. For example, Simelton et al. [92] observed that small droughts might have relatively large effects on crop yields in the face of inadequate adaptive capacity and vice versa because low adaptive capacity increases vulnerability. Socio-economic variables have been suggested for use as proxies for adaptive capacity in indicator-based approaches for

Months	J	F	M	A	M	J	J	A	S	O	N	D
Beans	Land preparation	Sowing	Growing	Growing	Harvesting	Dry in sun	Land preparation	Sowing	Growing	Growing	Harvesting	Dry in sun
Ground nuts	Land preparation	Land preparation	Sowing	Growing	Growing	Harvesting	Land preparation	Sowing	Growing	Growing	Harvesting	Harvesting
Sweet potato	Land preparation	Sowing	Growing	Growing	Growing	Harvesting	Harvesting	Land preparation	Growing	Growing	Growing	Harvesting
Cassava	Land preparation	Sowing	Growing	Growing	Growing	Growing	Growing	Growing	Growing	Growing	Harvesting	Harvesting
Maize	Land preparation	Sowing	Growing	Growing	Harvesting	Harvesting	Harvesting	Sowing	Growing	Growing	Harvesting	Harvesting
Millet	Land preparation	Sowing	Sowing	Growing	Growing	Harvesting	Harvesting	Sowing	Growing	Growing	Harvesting	Harvesting
Seasons	Dry		Rainy			Dry			Rainy		Dry	

Fig. 2 Regional crop calendar for all six crops

vulnerability assessment; some of these include: level of education and poverty, availability of safety nets, and transportation system [3, 6, 7, 15, 28, 47, 67, 95].

To assess the adaptive capacity of the crops used in this study, we adopted two socio-economic proxies of adaptive capacity: poverty (%) (Material asset) and literacy rates (%) (Human asset). Poverty rate in the context of this study refers to material than financial assets because; "...income poverty measures provide important but incomplete guidance to redress multidimensional poverty" [4]. Income shows higher rates of poverty than there really is and not all households can translate income into health or educational expenses [4]. The poverty rate data for the national and regional level models were culled based on indicators such as: size of household, type of floor, source of water, type of toilet, presence or absence of electricity Daniels [15]. The poverty rate and literacy rate data were collected from [15] and UBOS [98–101] in which literacy and poverty related data

are presented for different cropping systems, regions, districts, gender, ethnicities and ages, inter alia.

These two proxies of adaptive capacity were selected as the main socio-economic proxies because of limited data on the other potential proxies such as route network, safety nets, natural resources and because these two proxies adequately capture and impact all other proxies. For example, poverty reduction can lead to improvements in the literacy rates (human assets) and the spillover effects of this could be reflected in improved social connections, networks and safety nets (social assets), improved transport and route networks (physical assets), improved ownership of property (material assets), and improved disposable income (financial assets). The Government of Uganda is said to use growth in the agriculture sector to drive economic growth [49]. Poverty reduction among farming households will drive growth in other sectors in Uganda [15] and UBOS [98–101]. Also, ~ 87% of Ugandans live in rural areas and about 30% of all rural people (10 million

men, women and children) are still below the national poverty line. Reducing poverty through agriculture is the main avenue to developing other sectors [49]. For the adaptive capacity index (see Eq. 7).

$$ADTC_{xrn} = \left(\frac{10^2 - P_{rtrn}}{10^2} \right) + \left(\frac{L_{rtrn}}{10^2} \right) \quad (7)$$

where $ADTC_{xrn}$ is the crop yield adaptive capacity index, P_{rtrn} is the poverty rate (%), L_{rtrn} is the literacy rate (%).

4 Results

4.1 Vulnerability, sensitivity, exposure and adaptive capacity at the regional scale in Southwest Uganda

At the regional scale in Uganda, millet stands out as the most vulnerable crop with a vulnerability index of 1.08 (108%) (Fig. 3). The second most vulnerable crop in the series is maize with a vulnerability index of 0.90 (90%) while groundnuts have a vulnerability index of 0.70 (70%) (Fig. 3). Millet with the highest vulnerability index also records a relatively high sensitivity index of 1 (100%) (Fig. 3) and the highest level of exposure reflected in an exposure index of 1.57 (157%) (Fig. 3). Maize with the second highest vulnerability has a sensitivity index of 1 (100%) (Fig. 3) and a corresponding exposure index of 1.39 (139%) (Fig. 3). Finally, groundnuts, the third most vulnerable crop has a sensitivity index of 0.99 (99%) (Fig. 3) and an exposure index of 1.21 (121%) (Fig. 3). As concerns adaptive capacity, millet with the highest vulnerability index has the lowest adaptive capacity index of 1.49 (149%) (Fig. 3) while maize and groundnuts have slightly

higher adaptive capacity indices of 1.49 (149%) and 1.50 (150%) respectively (Fig. 3).

At a regional scale, the least vulnerable crops in order of magnitude of vulnerability indices are sweet potatoes with a vulnerability index of 0.16 (16%), cassava with a vulnerability index of 0.17 (17%) and beans with a vulnerability index of 0.59 (59%) (Fig. 3). Sweet potatoes with the lowest vulnerability index also records the lowest sensitivity and exposure indices of 0.95 (95%) and 0.74 (74%) (Fig. 3) respectively and the highest adaptive capacity index in the series of 1.53 (153%) (Fig. 3d). As the vulnerability indices rises, so also does the corresponding sensitivity, for example, in the case of cassava and beans (Fig. 3) and exposure (Fig. 3) indices. The adaptive capacity index of cassava is the same as that for sweet potatoes 1.53 (153%) while that for beans is 1.51 (151%) (Fig. 3). It can be said that at the regional scale in southwest Uganda, crops with the highest level of vulnerability equally have relatively higher sensitivity and exposure to climate change and variability and low adaptive capacity (Fig. 3). On the other hand, crops with lower vulnerability equally have relatively lower sensitivity and exposure and higher adaptive capacity (Fig. 3).

4.2 Scatter plots of vulnerability, sensitivity, exposure and adaptive capacity at the regional scale in South West Uganda

Apart from an observed inverse relationship between adaptive capacity and vulnerability (Fig. S4), adaptive capacity and exposure (Fig. S4) and adaptive capacity and sensitivity (Fig. S4) in which as adaptive capacity rises, vulnerability, exposure and sensitivity decrease, the rest of the scatter plots show a direct relationship between the concerned variables. When exposure increases, vulnerability increases (Fig. S4), when sensitivity increases, vulnerability also increases (Fig. S4) and when sensitivity increases, exposure also increases (Fig. S4). These results are realistic in the sense that it makes sense to argue that when the adaptive capacity is high there is a tendency for the crops in question to show more resilience and lower vulnerability, sensitivity and exposure. For all these scatter plots, the least coefficient of determination (R^2) is 0.52 or 52% in the case of the scatter plot of sensitivity against vulnerability (Fig. S4); the rest of the scatter plots have a reliability of above 0.90 or 90%, an indication that most of these models are reliable as they aptly explain the relationship between the variables concerned.

4.3 Vulnerability, sensitivity, exposure and adaptive capacity at the national scale in Uganda

At the national level in Uganda, the main difference from the southwestern scale is that cassava stands out as the

Fig. 3 Regional comparative representation of vulnerability, adaptive capacity, exposure and sensitivity indices of crop yields to droughts in Southwestern Uganda for the period 1998–2017

most vulnerable crop with a vulnerability index of 0.61 (61%) (Fig. 4) followed by beans with a vulnerability index of 0.55 (55%) and groundnuts with a vulnerability index of 0.52 (52%) (Fig. 4). Cassava with the highest vulnerability index also records a relatively high sensitivity index of 1 (100%) (Fig. 4) and the highest level of exposure reflected in an exposure index of 1.0 (110%) (Fig. 4). Beans, the second most vulnerability crop has the same sensitivity as cassava of 1.0 (100%) (Fig. 4) and an exposure index of 1.12 (112%) (Fig. 4). Finally, groundnuts have a sensitivity index of 0.99 (99%) (Fig. 4) and exposure index of 1.21 (121%) (Fig. 4). In the context of adaptive capacity, cassava with the highest vulnerability index has a low adaptive capacity index of 1.45 (145%) (Fig. 4) while beans and groundnuts record a relatively higher adaptive capacity index of 1.46 (146%) (Fig. 4).

In terms of least vulnerable crops, the national scale results differ from the southwestern results in that maize has the least vulnerability with an index of 0.33 (33%), millet with a vulnerability index of 0.38 (38%) and sweet potatoes with a vulnerability index of 0.42 (42%) (Fig. 4). Maize with the lowest vulnerability index also records a sensitivity index of 1.0 (100%) and an exposure index of 0.82 (82%) (Fig. 4) and the highest adaptive capacity index in the series of 1.49 (149%) (Fig. 4). As the vulnerability indices increase in the case of millet (0.38) and sweet potatoes (0.42), so also does the corresponding sensitivity (Fig. 4) and exposure (Fig. 4) indices. The adaptive capacity index of maize 1.49 (149%) is higher than that for millet 1.47 (147%) and sweet potatoes 1.46 (146%) respectively (Fig. 4). It can be said that at the national scale in Uganda, crops with the highest level of vulnerability equally have relatively higher sensitivity and exposure to climate change and variability and low adaptive capacity (Fig. 4). On the other hand, crops with lower vulnerability equally have relatively lower sensitivity and exposure and higher adaptive capacity (Fig. 4).

Fig. 4 National comparative representation of vulnerability, adaptive capacity, exposure and sensitivity indices of crop yields to droughts in Southwestern Uganda for the period 1998–2017

4.4 Scatter plots of vulnerability, sensitivity, exposure and adaptive capacity at the national scale in Uganda

Apart from an observed inverse relationship between adaptive capacity and vulnerability (Fig. S6), adaptive capacity and exposure (Fig. S6) and adaptive capacity and sensitivity (Fig. S6) in which as adaptive capacity increases vulnerability, exposure and sensitivity decrease, the rest of the scatter plots show a direct relationship between the concerned variables. When exposure increases, vulnerability increases (Fig. S6), when sensitivity increases, vulnerability also increases (Fig. S6) and when sensitivity increases, exposure also increases (Fig. S6). These results are realistic in the sense that it is right to argue that when the adaptive capacity is high there is a tendency for the crops to show more resilience and lower vulnerability, sensitivity and exposure. For all these scatter plots, a coefficient of determination (R^2) of more than 50 percent (except for those on Fig S6c, d, & f) is recorded meaning most of these models (except for the relationship between sensitivity and vulnerability and sensitivity and exposure) are reliable as they aptly explain the relationship between the variables concerned.

5 Discussion

This paper has shown that there is an inverse relationship between adaptive capacity on the one hand and vulnerability, exposure and sensitivity at both the national and regional scales in Uganda. The varying nature of the adaptive capacity index is anchored in variations in proxies of adaptive capacity such as poverty and literacy rates. For example, high poverty rates often coincide with low literacy rates. Low income farmers often have limited access modern farming equipment and planting materials, an issue that reduces their ability to adapt their cropping systems.

In Uganda, adaptive capacity is confounded by trends of declining precipitation across Uganda. Farmers that are unable to adapt have their crops exposed to the ravages of declining precipitation. It has been observed that climate change has effects on food security and declining precipitation and rising temperatures are among the most important climate change variables that champion this change [13, 36, 37, 42, 92, 97]. This finding is important because it alerts stakeholders on the possible outcomes of an already bad situation. Also, there is evidence aligned with the view that areas of high poverty and low literacy rates often have low adaptive capacity as they are poorly equipped to adapt and respond to climate change, climate variability or extreme events [20, 21, 82].

Socio-economic disparities between regions, communities and even countries can trigger differences in the ability to respond to changes in climate. In the context of Uganda, it has been argued that in 2010, the poverty rate in the north was 46.2% and higher than the 21.8% recorded in the south [15] thus rendering farmers in the north less vulnerable when compared to those in the south. Poverty reduces access to resources as poor communities have restricted access to inputs such as fertilizers, high yielding drought resistant crop species, and irrigation infrastructure [7]. In 2006, it was reported that the literacy rates in the south of Uganda were between 63 and 75% while in the north they ranged between 60% and 63% [98–101]. Such disparities in literacy rates render it difficult for farmers in areas with low literacy rates to be able to respond adequately to droughts either because of lack of basic education, indigenous knowledge or exposure to training. For example, IFAD [49] argues that small-holder peasant farmers in northern Uganda lack: vehicles and roads to transport their produce, technological inputs to increase production and reduce pests, have limited access to financial services that can boost their incomes and expand production. These findings are consistent to those from other studies [6–8, 16, 39, 71, 88]. In South Africa for example, vulnerability to droughts has been linked to the degree of socio-economic development; assets, whether financial, human, natural, physical and social do greatly affect the ability of communities to cope with climate change related problems [6–8, 16, 39, 71, 88].

Socially, it has been argued that in the face of droughts, well connected households rely on their friends and families for sustenance [81]. In countries with strong social safety nets, during hazards, shelter, food, clothing and even finances are placed at the disposal of the people. Financial assets such as savings, pensions and credit facilities increase a community's ability to absorb the shocks related to droughts [87]. Financial assets are limited by the fact that they tend to show higher rates of poverty than there really is. It is also difficult to translate income into health or educational expenses [4]. Farm to market roads/physical assets may predict how fast a community responds to climate change, climate variability and extreme events as seen in the degree of rapidity with which relief or external support gets to the affected communities [1, 3, 22, 47]. The literacy level thus however affects this response as well and could include for example education, indigenous knowledge and exposure to training (human asset) which can hamper the ability of farmers to comprehend climate change related information [83]. Being that there are several possible determinants of adaptive capacity, it is important to note that poverty and literacy rates are used as proxies of adaptive capacity. However, these two variables are highly representative

proxies of adaptive capacity because the government of Uganda has argued that it depends on poverty reduction in the agricultural sector and training of farmers to reduce poverty in Uganda [49].

The results from this study show some disparities from the national to the regional. For example, at the regional scale the most vulnerable crops are millet, maize and groundnuts while at the national scale the most vulnerable crops are cassava, beans and groundnuts. These differences can be explained by variations in scale from national to regional which can trigger differences in the response and adaptive capacity of crops to droughts. In other words, different crops respond differently, and this is due to internal variations in the scale of the data used in fitting the models for the different crops. Also, the internal variations of the different crops might have been triggered by variations in the growing seasons for the same crops at different scales of analysis, the reason why the same crops might have different levels of vulnerability at different scales of analysis. Sweet potatoes recorded the least vulnerability in the southwest of the country and this can be attributed to the increasing importance of the crop across Uganda. In fact, Uganda is the largest producer of sweet potatoes in Africa and third on the world chart after China and India. The crop generally grows all-over the country but most importantly in areas with fertile soils. The presence of fertile volcanic soils in western Uganda around Lake Edward with average productivity in the greater south can also explain the surge in the cultivation and resilience of sweet potatoes in that region. Fertile clay soils are also found in the southwest of the Nebbi district and around Jinja [57]. Also, the fact that Uganda is the largest producer of sweet potatoes in Africa shows that the crop has been valorized as it plays a major role in the diet and economy of the country. The use of high yielding varieties and drought tolerant species of the crop has gone a long way to complement the enhanced adaptive capacities recorded in the area.

At the national scale, maize is the least vulnerable crop. The increase valorization of the maize in Uganda can be because of several factors among which are: it is among the most widely cultivated crops in the world, it is affordable and most widely grown in most of Africa and Uganda [9, 23, 62], it constitutes a major part of the diet of the people of Uganda as it is consumed as staple fermented dough, roasted, used as corn porridge or converted into 'corn beer', maize is produced primarily (~90%) by small-scale peasant farmers [10, 22, 70, 73, 80], and Ugandan maize is also grown across the country in differing agro-climatic zones, requiring medium (500 mm/growing season month) to high (800 mm/growing season month) precipitation [70, 73]. So, it can be said that the crop has a high range of tolerance surviving under conditions of minimum

precipitation, thus the reason for the crop recording the lowest vulnerabilities at a national scale.

These findings have implications for agricultural planning as these vulnerability indices can be used to inform future planning in the context of improving the resilience of the more vulnerable crops by either introducing drought tolerant species or adjusting planting dates to avoid exposing the crops to too much stress. This paper is limited by the fact that the adaptive capacity index is based on the use of proxies such as literacy and poverty rates; these were however rationalised by the absence of more direct data to represent adaptive capacity. Also, the data range for this paper ends in 2017. Missing out on 2018 and 2019 trends which would deprive the results of more recent data.

6 Conclusion

This study has shown that at a regional scale, the most vulnerable crops are millet, maize and groundnuts while at the national scale the most vulnerable crops are cassava, beans and groundnuts. It is therefore recommended that more research be carried out on these more vulnerable crops to further identify options for creating resilience and producing high yielding drought resistant varieties. It is also important that finer scale studies at the grassroot level be carried out to verify how these crops operate at such scales, this might include experimental farms that simulate droughts at the catchment area scale. This is important because more specific small-scale studies may be able to track the local realities in the field that many regional and national scale studies like the current are unable to reflect. Furthermore, it will be important to use models that handle several environmental and human variables to verify the relative contributions of climatic and non-climatic drivers of specific crop yields at varying scales in Uganda.

Acknowledgements The authors wish to thank all the authors whose papers have been cited and two anonymous reviewers for comments and suggestions.

Funding The work is supported by IHACC 2.0.

Compliance with ethical standards

Conflict of interest The authors declare no conflicts of interest.

References

- Adger WN, Brooks N, Bentham G, Agnew M, Eriksen S (2004) New indicators of vulnerability and adaptive capacity in technical report, 7. Norwich, UK: Tyndall Centre for Climate Research
- Albizua A, Corbera E, Pascual U (2019) Farmers' vulnerability to global change in Navarre, Spain: large-scale irrigation as maladaptation. *Reg Environ Change* 19:1–12
- Alderman H, Babita M, Demombynes G, Makhatha N, Özler B (2001) How low can you go? Combining census and survey data for mapping poverty in South Africa. *J Afr Econ* 11(3):169
- Alkire S, Santos ME (2010) Acute multidimensional poverty: a new index for developing countries. OPHI working paper no. 38. Oxford Poverty and Human Development Initiative, Oxford
- Antwi-Agyei P, Fraser EDG, Dougill A, Stringer AJ, Simelton E (2012) Mapping the vulnerability of crop production to drought in Ghana using rainfall, yield and socioeconomic data. *Appl Geogr* 32:324–334. <https://doi.org/10.1016/j.apgeog.2011.06.010>
- Bangladesh Bureau of Statistics and United Nations world food programme (2004) Local estimation of poverty and malnutrition in Bangladesh. Bangladesh Bureau of Statistics, Dhaka
- Benson T, Chamberlin J, Rhinehart I (2005) An investigation of the spatial determinants of the local prevalence of poverty in rural Malawi. *Food Policy* 30(5–6):532–550
- Brooks N, Adger WN, Kelly PM (2005) The determinants of vulnerability and adaptive capacity at the national level and the implications for adaptation. *Glob Environ Change* 15:151–162
- Challinor A, Simelton ES, Fraser ED, Hemming D (2010) Increased crop failure due to climate change. Assessing adaptation options using models and socio-economic data for wheat in China. *Environ Res Lett* 5:034012
- Challinor A (2008) Towards the development of adaptation options using climate and crop yield forecasting at seasonal to multi-decadal timescales. *Environ Sci Policy*. <https://doi.org/10.1016/j.envsci.2008.09.008>
- Challinor A, Wheeler T, Garforth C, Kassam A (2008) Assessing the vulnerability of food crop systems in Africa to climate change. *Clim Change* 83(3):382–399
- Chen C, Noble I, Hellmann J, Coffee J, Murillo M, Chawla N (2015) University of Notre Dame global adaptation index country index technical report. http://index.nd-gain.org:8080/documents/nd-gain_technical_document_2015.pdf. Accessed 4 November 2018
- Comenetz J, Caviedes C (2002) Climate variability, political crises, and historical population displacements in Ethiopia. *Glob Environ Change Part B Environ Hazards* 4(4):113–127
- Cooper P, Dimes J, Rao K, Shapiro B, Shiferaw B, Twomlow S (2008) Coping better with current climatic variability in the rain-fed farming systems of sub-Saharan Africa: an essential first step in adapting to future climate change? *Agric Ecosyst Environ* 126(1):24–35
- Daniels L (2011) Measuring poverty trends in Uganda with non-monetary indicators. http://www.fao.org/fileadmin/templates/ess/pages/rural/uye_city_group/2011/documents/session3/Daniels_-_Paper.pdf. Accessed 12 October 2018
- Defiesta G, Rapera C (2014) Measuring adaptive capacity of farmers to climate change and variability: application of a composite index to an agricultural community in the Philippines. *J Environ Sci Manag* 17(2):48–62
- Department of Disaster Management, Office of the Prime Minister (2012) The 2010–2011 integrated rainfall variability impacts, needs assessment and drought risk management strategy. Office of Prime Minister of Uganda. http://gfdr.org/sites/gfdr/files/UGANDA_PDNA_Report_2012.pdf. Accessed 26 October 2018
- Duvick DN, Cassman KG (1999) Post-green revolution trends in yield potential of temperate maize in North-Central United States. *Crop Sci* 39:1622–1630
- Easterling WE, Aggarwal PK, Batima P, Brander KM, Erda L, Howden SM, Kirilenko A, Morton J, Soussan JF, Schmidhuber

- J, Tubiello FN (2007) Food, fibre and forest products. In: Parry ML, Canziani OF, Palutikof JP, Linden PJvd, Hanson CE (eds) *Climate change 2007 Impacts, adaptation and vulnerability. Contribution of working group II to the fourth assessment report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, pp 273–313
20. Epule TE, Ford JD, Lwasa S (2017a) Projections of maize yields vulnerability of maize yields to droughts and adaptation options in Uganda. *Land Use Policy* 65:154–163. <https://doi.org/10.1016/j.landusepol.2017.04.013>
21. Epule TE, Ford JD, Lwasa S, Lepage L (2017b) Vulnerability of maize yields to droughts in Uganda. *Water* 9:181. <https://doi.org/10.3390/w9030181>
22. Epule TE, Bryant CR, Akkari C, Daouda O (2015a) Can organic fertilizers set the pace for a greener arable agricultural revolution in Africa? Analysis, synthesis and way forward. *Land Use Policy*. <https://doi.org/10.1016/j.landusepol.2015.01.033>
23. Epule TE, Bryant CR (2015b) Maize production responsiveness to land-use change and climate trends in Cameroon. *Sustainability* 7:384–397. <https://doi.org/10.3390/su7010384>
24. Epule TE, Peng C, Lepage L, Chen Z (2014) The causes effects and challenges of Sahelian droughts: a critical review. *Reg Environ Change* 14(145–156):v. <https://doi.org/10.1007/s10113-0473-z>
25. Eriksen SH, Kelly PM (2007) Developing credible vulnerability indicators for climate change adaptation policy assessment. *Mitig Adapt Strateg Glob Change* 12:495–524
26. Farley C, Farmer A (2013) Uganda climate change vulnerability report, USAID. <http://community.eldis.org/5b9bfce3/ARCC-Uganda%20VA-Report.pdf>. Accessed 25 October 2018
27. Food and Agricultural Organization of the United Nations Statistics Division, FAO (2018a) FAOSTAT. <http://faostat3.fao.org/download/Q/QC/E>. Accessed 5 October 2018
28. Food and Agricultural Organization of the United Nations, FAO (2018b) Uganda crop calendar (major crops). <http://www.fao.org/giews/countrybrief/country.jsp?code=UGA>. Accessed 4 November 2018
29. Ford JD, McDowell G, Shirley J, Pitre M, Siewierski R, Gough W, Duerden F, Pearce T, Adams P, Statham S (2013) The dynamic multiscale nature of climate change vulnerability: an Inuit harvesting example. *Ann Assess Am Geogr* 103(5):1193–1211
30. Ford JD, Keskitalo ECH, Smith T, Pearce T, Berrang-Ford L, Duerden F, Smit B (2010) Case study and analogue methodologies in climate change vulnerability research. *Wiley Interdiscip Rev Clim Change* 1(3):374–392
31. Ford JD (2009) Vulnerability of Inuit food systems to food insecurity as a consequence of climate change: a case study from Igloolik. *Nunavut Reg Environ Change* 9(2):83–100
32. Ford JD, Gough WA, Laidler GJ, MacDonald J, Irngaut C, Qrunnut K (2009) Sea ice, climate change, and community vulnerability in northern Foxe Basin. *Can Clim Res* 38(2):137–154
33. Ford JD, Smit B, Wandel J, MacDonald J (2006) Vulnerability to climate change in Igloolik, Nunavut: what we can learn from the past and present. *Polar Rec* 42(02):127–138
34. Ford JD, Smit B (2004) A framework for assessing the vulnerability of communities in the Canadian Arctic to risks associated with climate change. *Arctic* 57(4):389–400
35. Fraser EDG (2007) Travelling in antique lands: using past famine to develop an adaptability/resilience framework to identify food systems vulnerability to climate change. *Clim Change* 83(4):495–514
36. Fraser EDG (2006) Agro-ecosystem vulnerability: using past famines to help understand how food systems may adapt to climate change. *J Ecol Complex* 3(4):328–335
37. Fraser E (2003) Social vulnerability and ecological fragility: building bridges between social and natural sciences using the Irish potato famine as a case study. *Conserv Ecol* 7(1):9
38. Fussel HM (2009) Development and climate change. Background note: review and quantitative analysis of indices of climate change exposure, adaptive capacity and sensitivity and impacts. World Development Report, Potsdam Institute of Climate Impact Research, PIK, Germany
39. Gbetibouo G, Ringler C, Hassan R (2010) Vulnerability of the South African farming sector to climate change and variability: an indicator approach. *Nat Res Forum* 34:175–187
40. Global Yield Gap Atlas, GYGA (2013) FAO crop calendars for maize, sorghum, millet, rice and barley. <http://www.yieldgap.org/gygamaps/pdf/Details%20on%20crop%20information%20to%20calibrate%20crop%20models%20for%20Uganda.pdf>. Accessed 1 November 2018
41. Government of Uganda, Ministry of Water and Environment (2008) Inception Report: climate change vulnerability assessment, adaptation strategy and action plan for the water resources sector in Uganda. One World Sustainable Investments, Directorate of Water Resource Management
42. Green R (1993) The political economy of drought in Southern Africa 1991–1993. *Health Policy Plan* 8(3):256–266
43. Giannini A, Biasutti M, Held IM, Sobel AH (2008) A global perspective on African climate. *Clim Chang* 90:359–383. <https://doi.org/10.1007/s10584-008-9396-y>
44. Giannini A, Saravanan R, Chang P (2005) Dynamics of the boreal summer African monsoon in the NSIPP1 atmospheric model. *Clim Dyn* 25:517–535. <https://doi.org/10.1007/s00382-005-0056-x>
45. Giannini A, Saravanan R, Chang P (2003) Oceanic forcing of Sahel rainfall on interannual to interdecadal timescales. *Science* 302:1027–1030
46. Hahn MB, Riederer AM, Foster SO (2009) The Livelihood Vulnerability Index: a pragmatic approach to assessing risks from climate variability and change—a case study in Mozambique. *Glob Environ Change* 19(1):74–88
47. Hentschel J, Lanjouw JO, Lanjouw P, Poggi J (2000) Combining census and survey data to trace the spatial dimensions of poverty: a case study of Ecuador. *World Bank Econ Rev* 14(1):147–165
48. Houghton JT, Ding Y, Griggs DJ, Noguer M, Van der Linden PJ, Xi-aosu D, Maskell K, Johnson CA (2001) The scientific basis. Contribution of working group I to the third assessment report of the intergovernmental panel on climate change. Cambridge University Press, Cambridge, p 881
49. IFAD (2012) Enabling poor rural people to overcome poverty in Uganda: rural poverty in Uganda. Rome, Italy. www.ifad.org. Accessed 5 November 2018
50. IPCC (2014) In: Barros VR, Field CB, Dokken DJ, Mastrandrea MD, Mach KJ, Bilir TE, Chatterjee M, Ebi KL, Estrada YO, Genova RC, Girma B, Kissel ES, Levy AN, MacCracken S, Mastrandrea PR, White LL (eds) *Climate change 2014: impacts, adaptation, and vulnerability. Contribution of working group II to the fifth assessment report of the intergovernmental panel on climate change*. Cambridge University Press, Cambridge
51. IPCC (2014b) *Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds)]. IPCC, Geneva, Switzerland, 151 pp
52. IPCC (2013) *Climate change 2013: the physical science basis. Contributions of the working group 1 to the fifth assessment report of the IPCC*. Cambridge University Press, Cambridge, pp 979

53. IPCC (2007) Climate change 2007: impacts, adaptations and vulnerability. Contributions of the working group 2 to the fourth assessment report of the IPCC. Cambridge University Press, Cambridge, p 976
54. Kamali B, Abbaspour KC, Lehmann A, Wehrl B, Yang H (2018) Uncertainty-based auto-calibration for crop yield-the EPIC + procedure for a case study in Sub-Saharan Africa. *Eur J Agron* 93:57–72
55. Kamali B, Abbaspour KC, Wehrl B, Yang H (2018) Drought vulnerability assessment of maize in Sub-Saharan Africa: insights from physical and social perspectives. *Glob Planet Change* 162:266–274
56. Kaizzi K (2018) Global yield gap atlas: Uganda. <http://www.yieldgap.org/gygamaps/excel/GygaUganda.xlsx>. Accessed 3 October 2018
57. Kaizzi K (2014) Application of the GYGA approach to Uganda. Uganda. <http://www.yieldgap.org/gygamaps/excel/GygaUganda.xlsx>. Accessed 3 November 2018
58. Kulcharik CJ, Serbin S (2008) Impacts of recent climate change on Wisconsin corn and soya bean yield trends. *Environ Res Lett* 3:034003. <https://doi.org/10.1088/1748-9326/3/034003>
59. Lobell DB, Schlenker W, Costa-Roberts J (2011) Climate trends and global crop production since 1980. *Science* 333(6042):616–620
60. Lobell DB, Burke MB (2009) On the use of statistical models to predict crop response to climate change. *Agric For Meteorol* 150:1443–1452
61. Lobell DB, Cahill K, Field CB (2007) Historical effects of temperature and precipitation on California crop yield. *Clim Change* 81:187–203
62. Lobell DB, Field C (2007) Global scale climate-crop yield relationships and the impacts of recent warming. *Environ Res Lett* 2:014002
63. Luers AL, Lobell DB, Sklar LS, Addams CL, Matson AP (2003) A method for quantifying vulnerability, applied to the agricultural system of the Yaqui Valley, Mexico. *Glob Environ Change* 13:e255–e267
64. McCarthy JJ, Canziani OF, Leary NA, Dokken DJ, White KS (eds) (2001) Climate change 2001: impacts, adaptation and vulnerability. Cambridge University Press, Cambridge
65. McSweeney C, Lizcano G, New M, Lu X (2010) The UNDP climate change country profiles: improving the accessibility of observed and projected climate information for studies of climate change in developing countries. *Bull Am Meteorol Soc* 91(2):157–166
66. Minot N B, Baulch, Epprecht M (2006) Poverty and inequality in Vietnam: spatial patterns and geographic determinants. Research report No. 148. International Food Policy Research Institute, Washington, DC. <http://www.ifpri.org/publication/poverty-and-inequality-vietnam-0>. Accessed 3 November 2018
67. Minot NM, Epprecht Tran TTA, Quang Trung L (2006) Income diversification and poverty in the northern uplands of Vietnam. Research report no. 145. International Food Policy Research Institute, Washington, DC. <http://www.ifpri.org/publication/income-diversification-and-poverty-northern-uplands-vietnam>. Accessed 3 November 2018
68. Mishra AK, Singh V (2010) A review of drought concepts. *J Hydrol* 391:202–216. <https://doi.org/10.1016/j.jhydrol.2010.07.012>
69. Mishra AK, Singh V (2011) Drought modeling—a review. *J Hydrol* 403:157–175. <https://doi.org/10.1016/j.jhydrol.2011.03.049>
70. Moss RH, Edmonds JA, Hibbard KA, Manning MR, Rose SK, van Vuuren DP, Carter TR, Emori S, Kainum M, Kram T, Meehl GA, Mitchell JFB, Nakicenovic N, Riahi K, Smith SJ, Stouffer RJ, Thomson AM, Weyant JP, Wilbanks TJ (2010) The next generation of scenarios for climate change research and assessment. *Nature* 463:747–756. <https://doi.org/10.1038/nature08823>
71. Moser CON (1998) The asset vulnerability framework: reassessing urban poverty reduction strategies. *World Dev* 26(1):1–19
72. Mubiru J, Banda EJB (2012) Monthly average daily global irradiation map for Uganda a location in the equatorial region. *Renew Energy* 41:412–415
73. Mutai CC, Ward MN (2000) East African rainfall and the tropical circulation/convection on intra-seasonal to inter-annual time-scales. *Am Meteorol Soc* 3:3915–3939
74. Müller C, Cramer W, Hare WL, Lotze-Campen H (2011) Climate change risks for African agriculture. *Proc Natl Acad Sci* 108(11):4313–4315
75. Nelson DR, Adger N, Brown K (2007) Adaptation to environmental change: contributions of a resilience framework. *Annu Rev Environ Res* 32:395–419
76. Nicholson SE, Trucker CJ, Ba MB (1998) Desertification, drought and surface vegetation: an example from the West African Sahel. *Bull Am Meteorol Soc* 79(5):815–829
77. O'Brien K, Eriksen S, Nygaard LP, Schjolden A (2007) Why different interpretations of vulnerability matter in climate change discourses. *Clim Policy (Earthscan)* 7(1):73–88
78. Parry ML, Rosenzweig C, Iglesias A, Livermore M, Fischer G (2004) Effects of climate change on global food production under SRES emissions and socio-economic scenarios. *Glob Environ Change* 14(1):53–67
79. Peng C, Ma Z, Lei X, Zhu Q, Chen Q, Wang W, Liu S, Li W, Fang X, Zhou X (2011) A drought-induced pervasive increase in tree mortality across Canada's boreal forests. *Nat Clim Change* 1:467–471. <https://doi.org/10.1038/NCLIMATE1293>
80. Poate CD (1988) A review of methods for measuring crop production from small-holder producers. *Exp Agric* 24:1–14
81. Pretty J (2003) Social capital and the collective management of resources. *Science* 302:1912–1914
82. Regan PM, Kim H, Maiden E (2018) Climate change adaptation and agricultural output. *Environ Change Reg.* <https://doi.org/10.1007/s10113-018-1364-0>
83. Rakodi C (1999) A capital assets framework for analysing household livelihood strategies: implications for policy. *Dev Policy Rev* 17:315–342
84. Robock A, Turco R, Harwell MA (1993) Use of general circulation model output in the creation of climate change scenarios for impact analysis. *Clim Change* 23:293–335
85. Sacks WJ, Deryng D, Foley JA, Ramankutty N (2010) Crop planting dates: an analysis of global patterns. *Glob Ecol Biogeogr* 19:607–620. <https://doi.org/10.1111/j.1466-8238.2010.00551.x>
86. Schlenker W, Lobell DB (2010) Robust negative impacts of climate change African agriculture. *Environ Res Lett* 5:014010
87. Scoones I (1998) Sustainable rural livelihoods: a framework for analysis in working paper, 72. Institute for Development Studies, UK
88. Sen AK (1981) Poverty and famines: an essay on entitlement and deprivation. Clarendon Press, Oxford
89. Sherman M, Ford JD, Lianos-Cuentas A, Valdivia MJ, IHACC Research Group (2016) Food system vulnerability amidst the extreme 2010–2011 flooding in the Peruvian Amazon: a case study from the Ucayali region. *Food Secur.* <https://doi.org/10.1007/s12571-016-0583-9>
90. Sherman M, Ford JD (2013) Market engagement and food insecurity after a climatic hazard. *Glob Food Secur* 2(3):144–155
91. Shi W, Tao F (2014) Vulnerability of maize yield to climate change and variability during 1961–2010. *Food Secur.* <https://doi.org/10.1007/s12571-014-0370-4>

92. Simelton E, Fraser EDG, Termansen M, Foster PM, Dougill AJ (2009) Typologies of crop-drought vulnerability: an empirical analysis of the socioeconomic factors that influence the sensitivity and resilience to drought of three major food crops in China (1961–2001). *Environ Sci Policy* 12(4):438–452
93. Sivakumar MVK, Das HP, Brunini O (2005) Impacts of present and future climate variability and change on agriculture and forestry in the arid and semi-arid tropics. *Clim Change* 70:31–72
94. Smit B, Wandel J (2006) Adaptation, adaptive capacity and vulnerability. *Glob Environ Change* 16(3):282–292
95. Smit B, Pilifosova O (2003) From adaptation to adaptive capacity and vulnerability reduction. In: Smith JB, Klein RJT, Huq S (eds) *Climate change, adaptive capacity and development*. Imperial College Press, London
96. Sullivan C (2002) Calculating a water poverty index. *World Dev* 30(7):1195–1210
97. Thomson H, Berrang-Ford L, Ford JD (2010) Climate change and food security in Sub-Saharan Africa: a systematic literature review. *Sustainability* 2:2719–2733
98. Uganda Bureau of Statistics (UBOS) (2018) Uganda national household survey 2016/2017. Kampala, Uganda; UBOS. https://www.ubos.org/wp-content/uploads/publications/03_20182_016_UNHS_FINAL_REPORT.pdf. Accessed 3 November 2018
99. Uganda Bureau of Statistics (UBOS) (2014) Uganda national household survey 2012/2013. Kampala Uganda; UBOS. https://www.ubos.org/wp-content/uploads/publications/04_20182_012_13_UNHS_Final_Report.pdf. Accessed 3 November 2018
100. Uganda Bureau of Statistics (UBOS) (2006) 2002 Uganda population and household census analytical report: education and literacy. Kampala, Uganda; UBOS. <http://www.ubos.org/onlinefiles/uploads/ubos/pdf%20documents/2002%20CensusEducAnalyticalReport.pdf>. Accessed 3 November 2018
101. Uganda Bureau of Statistics (UBOS) (2002) Uganda national household survey 2002/2003. Kampala Uganda; UBOS. https://www.ubos.org/wp-content/uploads/publications/03_2018unhs_200203_report.PDF. Accessed 3 November 2018
102. Wang B, Ding Q, Fu X, Jin K, Shukla J, Doblas-Reyes F (2005) Fundamental challenge in simulation and prediction of summer monsoon rainfall. *Geophys Res Lett* 32:15711. <https://doi.org/10.1029/2005GL022734>
103. Ward P, Lasage R (2009) Downscaled climate change data from the HADCM3 and ECHAM5 models on precipitation and temperature for Ethiopia and Kenya. Report W-09/05. <http://www.adapts.nl/perch/resources/downscaledclimatedataforethiopiaandkenya.pdf>. Accessed 13 June 2016
104. World Bank Group (2016) Climate change knowledge portal for development practitioners and policy makers. http://sdwebx.worldbank.org/climateportal/index.cfm?page=country_historical_climate&ThisRegion=Africa&ThisCCode=UGA. Accessed 3 November 2018

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.