Article

Recent Patterns of Exposure, Sensitivity, and Adaptive Capacity of Selected Crops in Cameroon

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Abstract: In most parts of sub-Saharan Africa, precipitation is impacted by climate change. In some countries like Cameroon, it is still not clear how maize, millet and rice will respond to changes in growing season precipitation. This work examines the exposure, sensitivity, and adaptive capacity of the above crops to droughts at both the national and sub-national scale. Crop yield data were culled from FAOSTAT while growing season precipitation data were culled from the database of UNDP/Oxford University and the climate portal of the World Bank. Adaptive capacity proxies (literacy, and poverty rate) were collected from KNOEMA and the African Development Bank. The analysis was performed using the vulnerability index equation. Nationally, millet has the lowest vulnerability and rice has the highest. At the sub-national scale, northern maize has the highest vulnerability followed by western highland rice. It is observed that when scales change, the crops that are vulnerable also change. However, at both levels vulnerability has an inverse relationship with adaptive capacity.

Keywords: patterns; sensitivity; exposure; adaptive capacity; vulnerability; precipitation maize; crop yields

1. Introduction

According to the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) temperatures are projected to increase in sub-Saharan Africa (SSA) by between 1.5–2.5 °C by 2050 based on the RCP 4.5 scenario [1]. Furthermore, SSA has witnessed increase in annual surface air temperatures between 0.2–2.0 °C [2]. These temperature trends have been associated with changes in growing season precipitation, reflected mainly in unreliable precipitation. These trends have triggered the vulnerability of cropping systems in SSA [2–6]. Changes in precipitation in Cameroon impact agriculture because in Cameroon because agriculture there is essentially rainfed [2–5]. Droughts have impacted the mean crop growing season precipitation in Cameroon which now stands at around 200 mm for maize, rice, and millet [5]. Across Cameroon, there is a spatial variation in precipitation between the north and south of the country [5,6]. In the northern Sahelian parts of the country, droughts are frequent and occur on a yearly basis, thus placing a lot of stress on crops [5,6]. Even though droughts are recurrent in Cameroon, the most recent and significant droughts were recorded between 2012–2015 in which tons of maize, beans, millet, and rice seeds and seedlings were damaged [3–6].

It has been argued that the current dilemma of changing growing season precipitation is made even more difficult as the drivers of the vulnerability of food systems in most African countries, including Cameroon, go beyond climatic variables and include inter alia several non-climatic variables such as soils, slopes, crop pests, use of fertilizers [6,7]. In this context and to better understand and estimate the level of vulnerability of a crop; it is important to use, test and develop novel approaches that reflect the role of climatic

and non-climatic variables [7–9]. These dynamics are disturbing as they are already having profound effects on agriculture which is the "life wire" of most SSA economies including Cameroon [1,3,4].

The use of an index that heralds the role of climatic and non-climatic variables is already gaining grounds in academic scholarship. For example, Epule et al. [5] developed a crop yield vulnerability index for maize yields to droughts in Uganda; this approach was later used by Epule and New [10] to assess the vulnerability of five crops in 2019 in that country. In the current study this index is tested for several crops to depict sensitivity, exposure and the adaptive capacity in Cameroon. There are other indices that have been developed: the Global Notre-Dame (ND-Gain) adaptation index [11], the crop-drought indicator [12], the water-poverty index, which shows vulnerability to access water based on poverty [13] and the farmer vulnerability to global change index which focuses on large scale irrigation and maladaptation [14].

The current index is mostly applicable in assessing vulnerability of cropping systems to droughts in an African crop production context by incorporating crop yield, climatic and adaptive capacity data. Its effectiveness has been tested mostly on maize, beans, cassava, groundnuts, potatoes, millet, and sweet potatoes in Uganda [5,10]. This approach is advantageous as it can respond to the needs of providing a holistic approach and integrating climatic and socio-economic variables into vulnerability mapping and assessments. In addition, it uses historical data which reflects ground truthing and the actual stress that the cropping systems might be subjected to [15]. The adaptive capacity part of this index focuses on the use of two proxies of adaptive capacity that are most relevant in the cropping systems equation of the country; these are literacy and poverty rates [16].

This work aims at testing the vulnerability index by simulating the relative vulnerability to growing season precipitation of maize, millet, and rice at a national scale in Cameroon and to socio-economic proxies like literacy and poverty rates. This work further validates the national scale perspective at four sites in Cameroon based on the availability of data. In other words, this study's objective is to assess the vulnerability of maize, millet, and rice in Cameroon by assessing the sensitivity, exposure, and adaptive capacity of these crops based essentially on growing season precipitation and two socio-economic proxies. The goal is therefore to use the findings to inform and support policy towards revamping the most vulnerable of these three crops and in providing a better understanding of the dynamics herein. As a country in SSA, Cameroon is both a breadbasket and a country which is invariably affected by climate change [17]. The country shows huge changes in annual precipitation across its agroecological zones. For example, annual precipitation varies from about 3000 mm in the southwestern Cameroon plateau to close to 500 mm in the extreme north of the country. Such variations are likely to be equally reflected in the growing season precipitation of many crops which are often impacted by recurrent droughts [1].

This work is rationalized by the fact that 1. maize, millet, and rice are among the most widely cultivated and affordable crops in Cameroon [17,18]; 2. these crops are among the most consumed staple foods in Cameroon [18]; 3. the cultivation of these crops is essentially in the hands of small-scale peasant farmers who are inadequately equipped to adapt to changes caused by climate [19,20] and lastly, 4. huge gaps still exist in the context of analyzing the vulnerability of these crops to droughts in Cameroon. Apart from a study by [18] that addresses the role of climatic and non-climatic drivers of maize yields in Cameroon, to the best of our knowledge there are no other studies that have used this vulnerability index to assess the relative vulnerability of these three crops in Cameroon. Aside from the Ugandan case study, this approach has never been used before. However, other studies that have used similar approaches include those by Mishra and Singh, [21,22] who focus on precipitation deficits and temperature changes, Kamali et al. [23,24] who used social and physical perspectives to evaluate the vulnerability of maize yields to droughts in Africa, and Jassogne et al. [25] and Mwaura and Okoboi [26] who also used crop-climate interactions. In addition to climate, the spatial distribution of soil types also affects crop production. For example, in the northern part of the country the soil types are essentially

sandy chromic vertisols, planosols and albic and stagnic luvisols which generally have a low moisture-holding capacity [27]. In the south, the soils are much richer and include dystric vitric andosols as well as leptic fragic umbrisols, this last category of soils have a higher moisture-holding capacity [27]. The section that follows discusses the conceptual dimensions and methodological aspects of this study.

2. Concepts, Materials and Methods

2.1. The Concept of Vulnerability

The term vulnerability describes the extent to which a system is susceptible and unable to cope with the negative effects of climate change and extreme weather episodes [2,28] (Figure 1). In the context of crop yields, vulnerability is the extent to which crops cope with multiple stressors and shocks that are climatically and socio-economically driven. Based on the following studies [1,3,12,28,29], vulnerability is driven by: (1) the level of *exposure* [29,30]; (2) the *sensitivity* [29,30], and (3) the *adaptive capacity*, which is determined by the ability of the farmers involved to absorb the water stress caused by variations in precipitation [30–33]. Previously, other indices that assess vulnerability at different levels have been developed as follows: The Global Notre-Dame (ND-Gain) adaptation index [11] which also has components of exposure, sensitivity, and adaptive capacity from which this current index was developed. However, it differs from the current in that it is broader and covers other sectors of vulnerability such as health, ecosystems, habitat, water, and infrastructure. Furthermore, the crop-drought indicator which provides indicators of vulnerability to droughts [12], the water-poverty index which shows vulnerability in the context of accessibility to water based on poverty [13] and the farmer vulnerability to global change index which focuses on large scale irrigation and maladaptation and associated vulnerability [14] (Table 1).
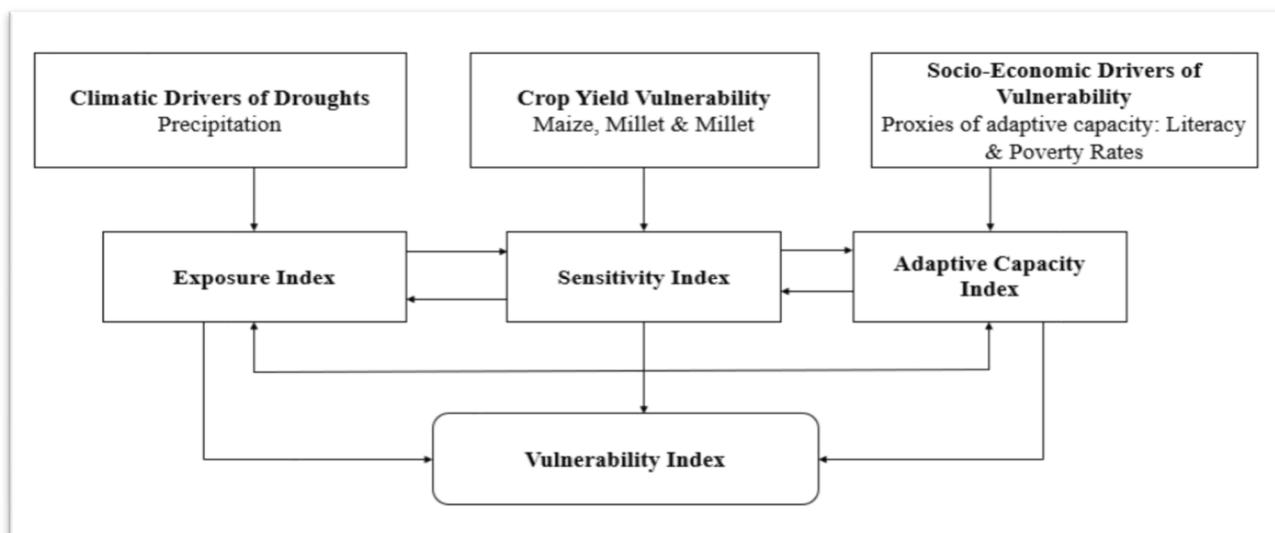
Figure 1. Schematic Representation of the Vulnerability Index.

The ND Gain index is one of the best-known vulnerability indices. It simulates a country's current vulnerability to climate change disruptions and assesses the country's readiness to leverage private and public sector investments for adaptive purposes. This index is one of the gold standards of creating vulnerability indexes. It has a component that assesses readiness for adaptation based on social, economic and governance. This aspect is far from our own index which essentially focuses on crop vulnerability and its three measures within an agricultural context. In creating this current index, the initial study focused on the food sector aspect of the ND Gain index and does not simulate the other sectors identified by ND Gain. Just like in our own vulnerability index, the ND Gain uses proxies for adaptive capacity, and estimates exposure, and sensitivity (Table 1).

Table 1. Other vulnerability indices.

Indices	Characteristics/Citations
The Global Notre-Dame Adaptation Index-ND Gain	Evaluates readiness for adaptation [11] Leverages public and private sector investments [11] Considers the following sectors: Health, Food, Ecosystem, Habitat, Water, and Infrastructure [11] Frames vulnerability as a function of exposure, sensitivity, and adaptive capacity [11]
The Crop-Drought Indicator	Uses indicators of vulnerability such as precipitation and temperature [12]
Water Poverty Index	Bases vulnerability on poverty [13] Considers water resource stress as an additional component of vulnerability [13]
Farmer Vulnerability to Global Change Index	Focuses on agricultural adaptations that result in maladaptation [14] Irrigation projects as agents of maladaptation [14]
Vulnerability Index of Crop Yields to droughts **	Vulnerability is framed as a function of exposure, sensitivity, and adaptive capacity [5,10] Focus on the interactions between crops, climate, and socio-economic drivers [5,10] Adaptive capacity framed based on African realities [5,10]

** Applied in current study.

Framing vulnerability as a function of sensitivity, exposure, and adaptive capacity can be rationalized as follows, (1) It incorporates an integrated approach which further enhances a holistic perspective. In the context of this study, the vulnerability index reflects the role of historical crop yields, historical precipitation, and socio-economic proxies of adaptive capacity [33,34]. (2) Secondly, the approach adopted also enhances the quantification of variables such as the adaptive capacity that is difficult to represent. In most of Africa, the difficulty of having data on adaptive capacity has made estimating it daunting and has made scientists to resort to the use of proxies. This study uses the two most important proxies of adaptive capacity in Cameroon which are literacy and poverty rates. (3) Thirdly, this approach conceptualizes vulnerability in a more fundamental and practically useful fashion. The results of the assessment and the indicators selected to assess vulnerability can be analyzed to identify the drivers of vulnerability. Addressing the drivers of vulnerability provides a reliable approach to reduce the current vulnerability and manage potential risks [34].

2.2. The Concepts of Sensitivity and Exposure Indices

The sensitivity index is the measurable decline in crop yields due to climate stressors and extreme events [2,28–30]. In other words, sensitivity is the manifestation of climate change, climate variability, and extreme events on crop yields. Therefore, the sensitivity index focuses on the actual yield responses to growing season precipitation. Theoretically, the sensitivity index (crop vulnerability) has a direct relationship with the exposure index (drought vulnerability) mainly through evapotranspiration. This is seen as crops might carry out transpiration at varying rates thereby affecting the amount of moisture lost to the climate system or may shade the ground depending on their canopies and thereby affecting evaporation [2]. Also, the roots of crops might enhance evaporation by making the soil porous and exposing it to evaporation [2,29,30]. It is important to emphasize here that this current study does not focus on the aspects of causality between these variables but simply describe the theoretical relationships that is observed. The exposure index further describes the extent and nature of the stimulus reflected in the magnitude, intensity, and duration of the moisture deficit [2,28–30] (Figure 1). The exposure index focuses on the actual precipitation responses to changes in climate. These two sub-indices tend to have a direct relationship with vulnerability index which implies causality and an

inverse relationship with the adaptive capacity index which does not imply causality. This relationship is inverse because when these two sub-indices are high the adaptive capacity index is low because the concerned farmers are unable to adequately respond/cope to the yield and precipitation declines due to low adaptive capacity. In other words, farmers who are less likely to adapt due to low adaptive capacity are more likely to suffer from the effects of declining yields and precipitation. The observed inverse relationship does not imply causality. Low adaptive capacity index can only indirectly impact exposure and sensitivity indices by affecting the ability of the farmers to adapt to changes in exposure and sensitivity. This can be reflected in land use practices which maladapt the farmers to the changes in exposure and sensitivity.

### 2.3. The Concept of Adaptive Capacity Index

The adaptive capacity index describes the ability of a production system to adjust or adapt or cope with multiple stressors and shocks including climate change, climate variability, and extreme events [2,29,30]. When linked to this study, the intensity of the effects of droughts on crop yields is often mitigated by the adaptive capacity of the farmers producing the crops to manage the drought. This adaptive capacity is often reflected in proxies such as literacy and poverty rates (Figure 1). The socio-economic proxies of adaptive capacity are the level of literacy and poverty which are safety nets in the face of climate stressors [35,36]. The adaptive capacity index does not affect the exposure, sensitivity, and vulnerability indices directly; it does so indirectly through it proxies such as literacy and poverty rates. However, the adaptive capacity index has an inverse relationship with the vulnerability index, exposure index, and the sensitivity index. This inverse relationship does not imply direct causality as adaptive capacity can only impact these other indices indirectly. When the adaptive capacity index is low, it means the farmers concerned have lower literacy levels and higher poverty levels and this is often associated to a higher exposure index reflected in a limited ability to adapt. Also, a low adaptive capacity index is associated to a higher sensitivity index which is reflected in the limited ability of the farmers to invest in options that will enhance crop yields such as high yielding varieties, fertilizers or even tractors. Furthermore, a low adaptive capacity index is associated with a high vulnerability index; this is also judged by the prevalence of higher poverty rates and low literacy rates which are associated with higher vulnerability due to increase exposure and limited ability to cope with precipitation and yield deficits. All these sub-indices (sensitivity, exposure, and adaptive capacity) together lead us to what is the vulnerability index. It is important to observe that the adaptive capacity index is an exogenous index that is influenced by external explanatory variables such as literacy and poverty rates.

2.4. Study Site

In 2019 the population of Cameroon was estimated at about 25 million [37]. It is situated between latitudes 1.7° N–13.8° N and longitudes 8.4° E–16.8° E [38]. It is bordered in the south by Equatorial Guinea, Gabon, and Congo, to the east by Central African Republic and Chad, to the north by Chad and to the west by Nigeria. In Cameroon agriculture is the main primary industry employing between 65–70% of the population. It accounts for about 52% of the GDP, about 45% to export earnings and 15% to public revenue [38]. Agriculture in Cameroon is rainfall dependent and is essentially carried out by small-scale peasant farmers.

Cameroon has the humid forest agroecological zone which is divided as follows: humid forest in the southern-central-eastern part of the country and a bi-modal precipitation, the western highland in the north-western part of the country. In the north can be found the High Guinea Savana around the Adamawa Region and the Sudano-Sahelian region that stretches up to the Lake Chad region. There is a decline in precipitation from the south to the north of the country. This also occasions changes in the types of crops that are grown across the country [38]. The south generally supports the cultivation of tubers and some grains like maize while in the north, the agroecological properties favor the cultivation of

mostly grains/cereals (Figure 2). However, in Cameroon maize is cultivated in both the south and north of the country while millet is cultivated essentially in the north (Adamawa, North and Far North Regions). The most important zones of rice cultivation are the Western Highlands (North West and Western regions). However, rice is also cultivated in smaller quantities in other regions in the north of the country (North and Far North Regions) as well as in smaller areas in the Centre Region, the South East and East Regions. In general, most of these crops are cultivated in the often dry and drought stricken northern parts of the country.
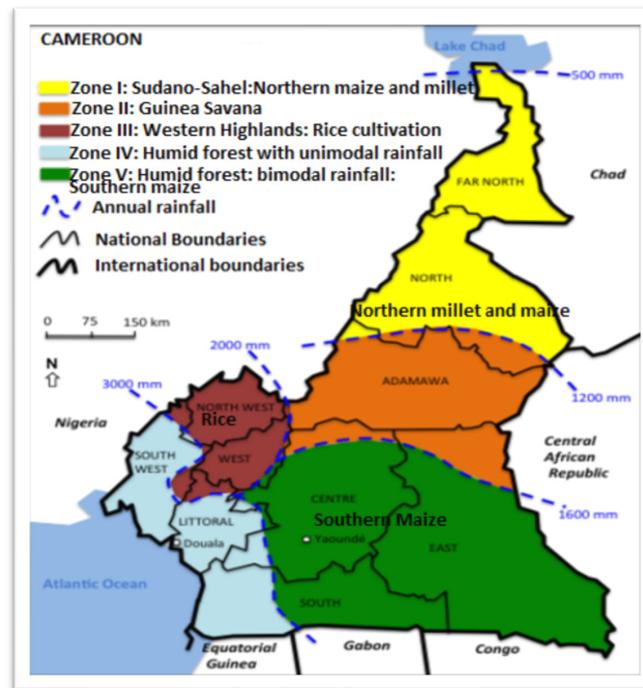
Figure 2. Agroecological Zones of Cameroon.

2.5. Data Types and Sources

The spatial dimension of this study is essentially national and sub-national. The sub-national scale was based on the availability of data for four sites at the sub-national scale for the various crops. Data on the various sub-components of vulnerability were collected. To compute the sensitivity indices to droughts at the national scale, time series data on observed crop yield for all three crops (maize, millet, and rice) for the period 1961–2019 in hg/ha/year were collected from FAOSTAT [39]. To validate the national scale sensitivity index, sub-national scale crop yield data (hg/ha/year) were found for four sites in Cameroon, these include: southern maize, northern maize, western highland rice, and northern millet. These sites are consistent with the zones in which these crops are predominantly cultivated. Unfortunately, the time series is only available for the period 1991–2016 [39].

The exposure indices at the national scale analysis were computed from the annual mean precipitation data and specific mean crop growing season precipitation data for the period 1961–2019 for each crop. These station-based data were collected from the collaborative database of the University of Oxford and UNDP [40–43] and the Climate Change Knowledge Portal of the World Bank Group [37]. Since the growing seasons of these crops are different; crop calendars for these crops were inspired from [44,45]. The final mean crop growing season calendars for rice, maize and millet in Cameroon are presented in Figure 3. Therefore, the mean crop growing season precipitation data for each year was a mean aggregate for the growing season months of that year. To validate the national scale exposure index, sub-national mean annual precipitation and mean annual crop growing

season precipitation data were downloaded from the Climate Change Knowledge Portal of the World Bank Group [37]. The four sites in which maize, millet and rice are mostly cultivated in Cameroon include: southern maize, northern maize, western highland rice, and northern millet. The time series data were collected for the period 1991–2016, consistent with the period in which crop yield data are available. It is important to note that maize has a bi-modal growing season in the south and a uni-modal growing season in the north of the country. As regards to millet, there is a uni-modal growing season in the north and central part of the country. In the case of rice, both the south and the western highlands have a uni-modal growing season (Figure 3). Theoretically, the areas with bi-modal growing season are likely to a lower vulnerability, sensitivity, and exposure indices while the reverse is true for the uni-modal areas.
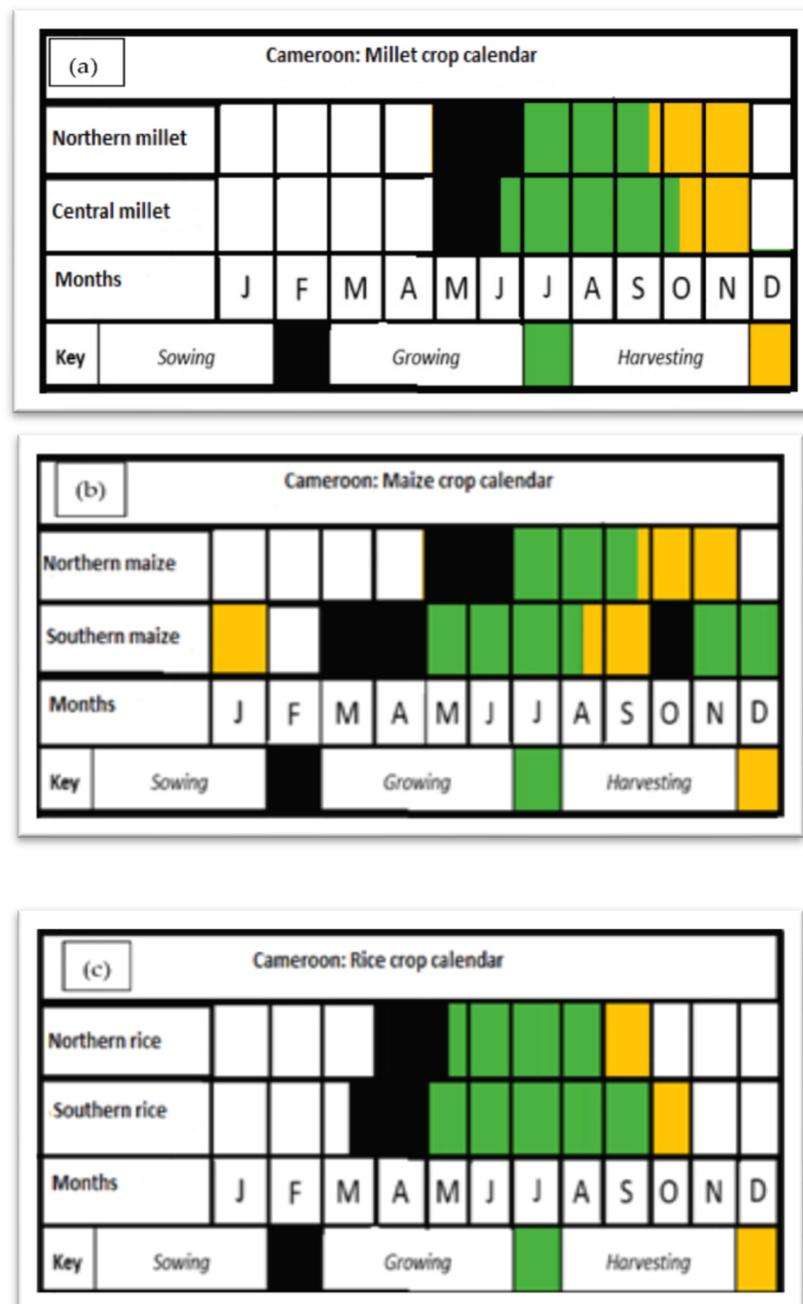

Figure 3. Growing Seasons for (**a**) Maize, (**b**) Millet and (**c**) Rice.

The adaptive capacity index was represented by two proxies which include: poverty (%) (material asset) and literacy rates (%) (human asset). The poverty rate includes both material and financial assets which are complete reflections of a people's ability to adjust to climate shocks by building resilience and adopting alternative livelihood sustenance options. The poverty rate data and literacy rate data for the national scale simulations were collected for the period 1961–2019 while those for the four sub-national scale sites were collected for the period 1991–2016 from the African Development Bank [46] and [47,48] respectively. These two socio-economic proxies are among the best that describe the variations in adaptive capacity and how these might impact resilience to climate shocks in predominantly crop production economies like Cameroon.

The vulnerability index was based on the data collected for all the three indices described above. This includes: the sensitivity, exposure, and adaptive capacity indices. This approach is mandated by the fact that vulnerability is usually a function of the above three indices. For details on how this was simulated, see the section on data analysis below.

2.6. Data Analyses

2.6.1. Vulnerability Index

The empirical vulnerability index was computed at the national scale and sub-national scale, this study uses a composite vulnerability index which was first developed by [5]. This index is like other vulnerability indices such as the ND-GAIN [11], the crop-drought indicator [12], and the water-poverty index [49–51]. This current index is unique because it is developed specifically for application in an African crop farming context. This index captures crop-specific parameters such as yield, precipitation, and the adaptive capacity of the farmers. All these computations were performed in excel and SPSS version 20. The equation used to compute this composite index is given below (Equation (1)).

$$VU_{xinsn} = SE_{xinsn} + EX_{xinsn} - AdC_{xinsn} \tag{1}$$

where VU_{xinsn} is the crop yield vulnerability index for the selected crops (rice, maize, and millet) at both national and sub-national scales, SE_{xinsn} is the crop yield sensitivity index at both national and sub-national scale, EX_{xinsn} is the crop yield exposure index at both national and sub-national scales and AdC_{xinsn} is the crop yield adaptive capacity index at both national and sub-national scales. Also, x is the year and i is a given crop.

2.6.2. Sensitivity Index

To determine the sensitivity index, the time series historical observed crop yield data for the national scale analysis for the period 1961–2019 and the sub-national scale analysis for the period 1991–2016 were subjected to detrending. This involves removing a linear model in the time series data by dividing the projected linear trend by the observed linear trend using Equation (2) below. The advantages of detrending are the ability to remove the repercussions of increased technology, ability to illustrate annual crop yield variations driven by precipitation and reduce the effects of consistency errors in reporting [5,17,31,52]. The trend line equations for a simple linear regression (Equation (2)) were used to project and obtain the projected or expected crop yields for each year for each of these crops. The observed and projected crop yield data were regressed against the precipitation data to determine their relationships with precipitation. The trend line equation is based on the ordinary least squared method. The sensitivity indices for the various crops were fitted by dividing the mean expected crop yields by the mean observed crop yields (Equation (3)). This approach is likened to that used by previous studies [5,12,53]. The polynomial model was subsequently used because the trends of rice were non-linear and therefore to better optimize the model a polynomial model was selected.

$$EXP_{xynsn} = ax + b. \tag{2}$$

where EXP_{xynsn} is the expected crop yield at both the national and sub-national scale, x is the year, a is the linear trend, b is the intercept when $EXP_{xyrnsn} = ax$.

$$SE_{xynsn} = \frac{EXP_{xynsn}}{ACT_{xynsn}} \tag{3}$$

where SE_{xynsn} is the crop yield sensitivity index at both national and sub-national scale, EXP_{xynsn} is the mean projected or expected crop yield at both national and sub-national scale, ACT_{xynsn} is the mean actual crop yield at both national and sub-national scale. y trepresents the yield and x the years notation.

2.6.3. Exposure Index

The exposure index was computed by dividing the mean annual monthly precipitation for the period 1961–2019 for the national scale analysis and for the period 1991–2016 for the sub-national scale analysis by the mean growing season precipitation for each crop during the period 1961–2019 for the national scale analysis and 1991–2016 for the subnational scale analysis. This is like methods used in other studies [5,12,54]. The growing season precipitation better reflects the actual growing conditions for the crop [55]. Equation (4) below was used to fit the exposure index.

$$EX_{xpnsn} = \frac{\mu LT_{annualppt(1961\ to\ 2019/1991-2016)}}{\mu STY_{growingSppt(1961\ to\ 2019/1991-2016)}} \tag{4}$$

where EX_{xpnsn} is the crop yield exposure index at both national and sub-national scale, $\mu LT_{annualppt(1961\ to\ 2019/1991-2016)}$ is the mean annual monthly precipitation at both national and sub-national scale, $\mu STY_{growingSppt(1961\ to\ 2019/1991-2016)}$ is the mean growing season precipitation at both national and sub-national scale. x and p represent years and precipitation, respectively.

2.6.4. Adaptive Capacity Index

Adaptive capacity index (see Equation (5)) was parameterized using two proxies: poverty and literacy rates. These two proxies were selected because data on the other potential proxies, such as route network, safety nets, natural resources are limited. Also, these two proxies adequately capture adaptive capacity and affect all other proxies. For example, poverty reduction can lead to improvements in the literacy rates (human assets) and the spill-over effects of this could be reflected in improved social connections, networks, and safety nets (social assets). Though these proxies have an inverse relationship, they are not entirely independent. Reducing poverty can enhance literacy rates and improve resilience to climatic shocks through climate knowledge accessibility and other means to invest in more resilient cropping systems. The equation used is presented below (Equation (5)).

$$AdC_{xnsn} = \left(\frac{10^2 - P_{xtnsn}}{10^2} \right) + \left(\frac{L_{xtnsn}}{10^2} \right) \tag{5}$$

where AdC_{xnsn} is the crop yield adaptive capacity index at both national and sub-national scale, P_{xtnsn} is the poverty rate (%) at both national and sub-national scale, L_{xtnsn} is the literacy rate (%) at both national and sub-national scale and x represents the year notation.

3. Results

3.1. Recent National Scale Trends in Maize, Millet and Rice Yields in Cameroon

Firstly, this study shows that maize and millet have consistently increased over time with the exceptions of some blips. For example, between 1961–2019, maize yields increase by 150% from above 6000 (hectograms per hectare: hg/ha) in 1961 to slightly above 15,000 hg/ha in 2019 (Figure 4a). This increase was occasioned by blips with the most prominent being a recurrent decline from the year 2000 from about 25,000 hg/ha to

16,264 hg/ha in 2019, a 34% decline. Millet on the other hand also witnessed an increase of 55.56% from above 9000 hg/ha in 1961 to about 14,000 hg/ha in 2019 (Figure 4b). Even though millet witnessed declining blips in 1986, 1990 and 2008, the subsequent yields showed recovery and continuous increase in production. Rice on its part witnessed an increase from about 4800 hg/ha in 1961 to about 56,000 hg/ha in 1989. Subsequently, the crop tilted towards a consistent decline ending at about 11,664 hg/ha in 2019 (Figure 4c).
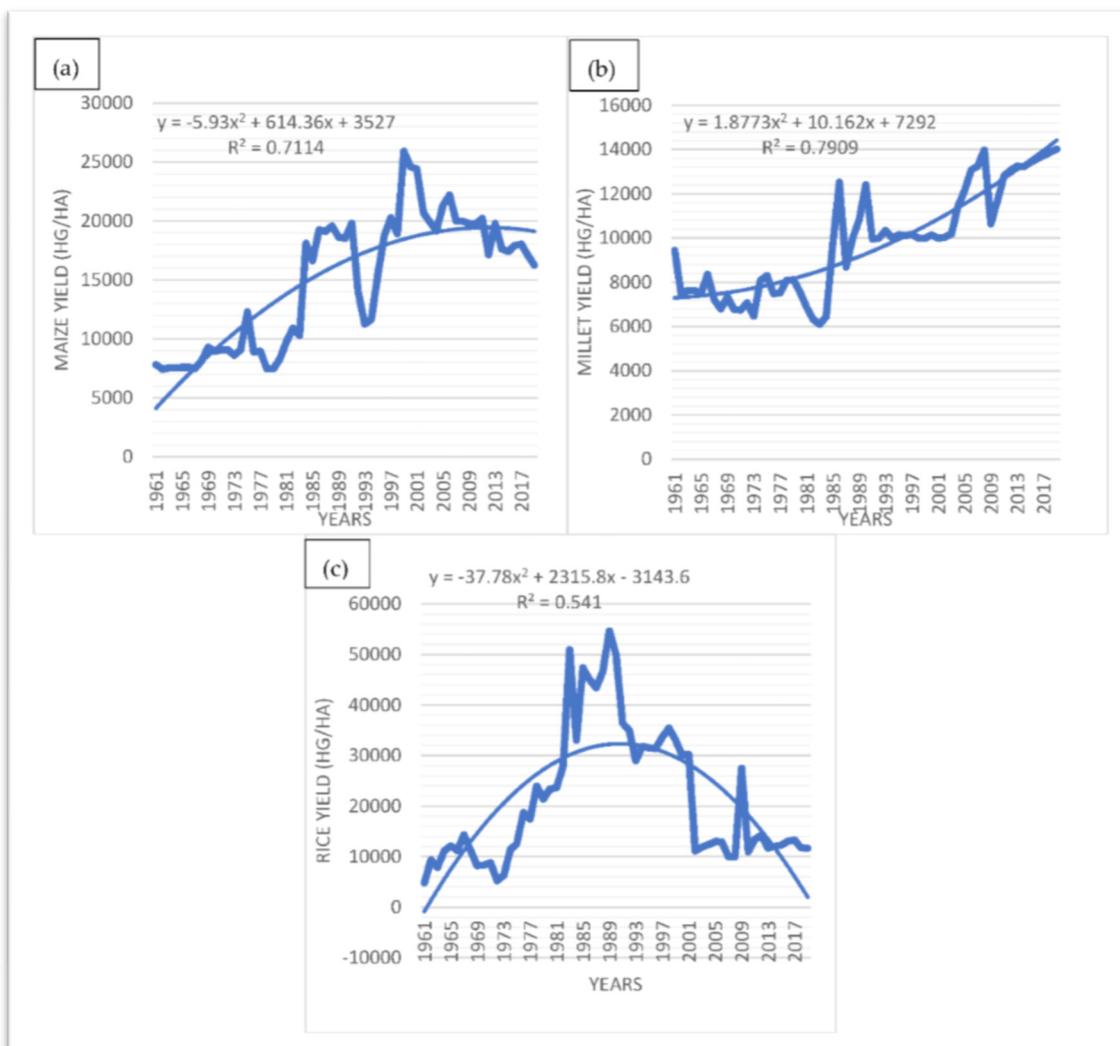

Figure 4. Polynomial regressions at a National Scale for (**a**) Maize (**b**) Millet and (**c**) Rice yield.

Among the three crops described above, millet had the highest coefficient of determination (R^2) of about 79%. Maize has an R^2 of about 71% while rice has and R^2 of about 54%. With an R^2 of about 79%, this study has found that in the context of millet, the model and data used explains about 79% of the variability of the response data around its mean (Figure 4b). Maize on the other hand also has an R^2 of about 71% which also indicates that the model explains about 71% of the variability of the response data around the mean (Figure 4a). Rice has the lowest R^2 of 54% which reflects an average relationship (Figure 4c). In addition to millet having the highest R^2, it also has a higher slope and intercept when compared to the other crops. Rice on its part has the lowest R^2 as well as slope and intercept.

3.2. Recent National Scale Trends in Maize, Millet and Rice Growing Season Precipitation in Cameroon

Results for the observed trends in growing season precipitation for the three crops show some variations. The mean growing season precipitation for millet straddles around 200 mm (Figure 5a) while that for maize straddles around 175 mm (Figure 5b). Rice which experiences a declining trend is less resilient, more vulnerable, and has a mean precipitation of about 200 mm (Figure 5c) much higher than that for maize. It is important to note that this depicts the fact that the different crops have different growing seasons and as a result the mean growing season precipitation for rice might be higher than that for maize, yet rice is still vulnerable. Secondly, this underscores the fact that even though precipitation levels are significant moisture requirement determinants for any crop, other variables are often needed to create a better understanding. In addition, this is also dependent on the distribution of the precipitation and the occurrence of outliers.
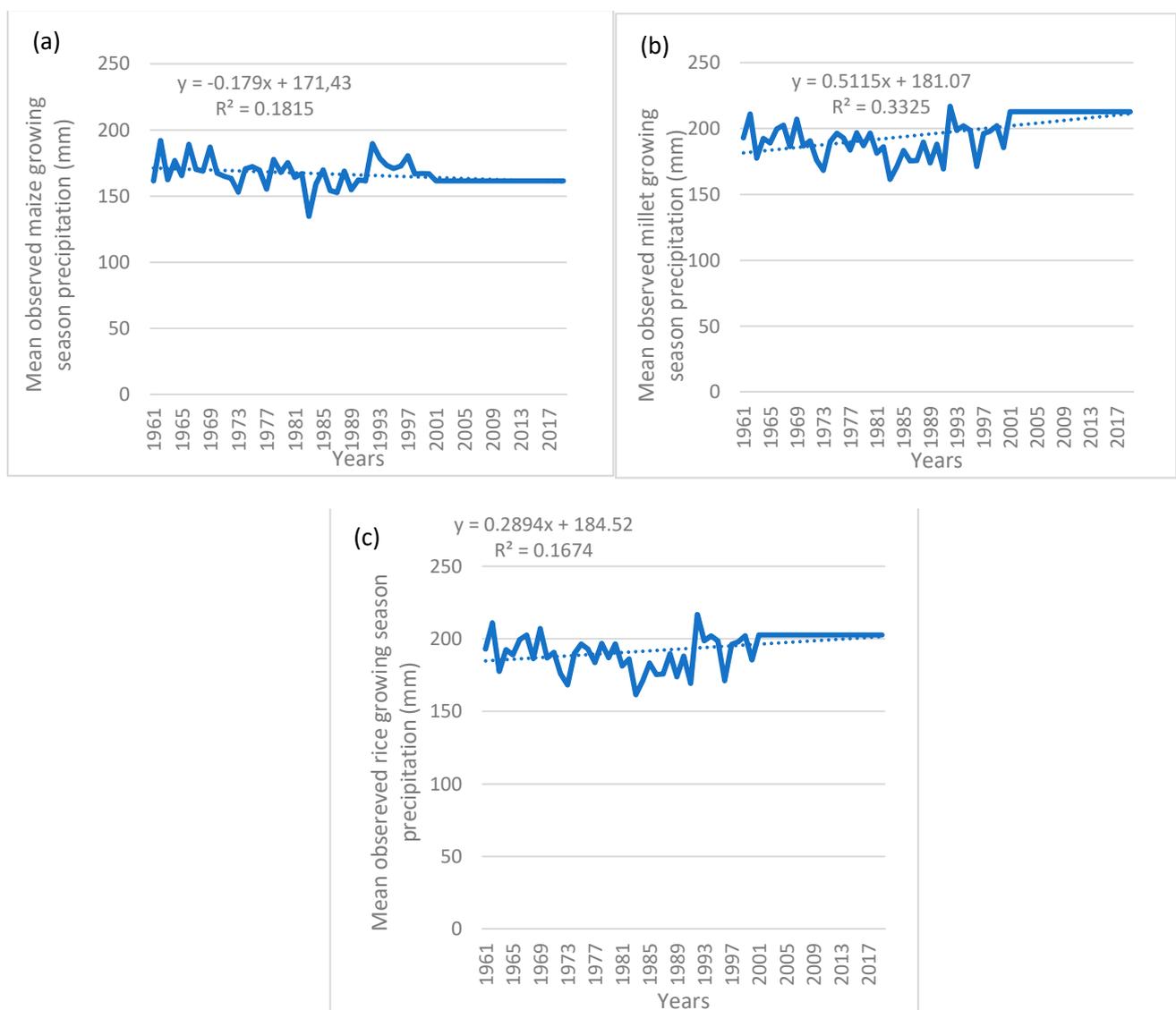
**Figure 5.** Growing Season Precipitation at a National Scale for (**a**) Maize, (**b**) Millet and (**c**) Rice.

The growing season precipitation averages about 200 mm because it is based on: 1. Only the mean for the growing season months of each crop which varies and is often shorter than the annual values, 2. Also, the growing season precipitation used here reflects

mostly data based an aggregate mean that reflects all the crop calendars across the country and 3. Most of these grains are cultivated in the northern regions of Cameroon which are often hit by recurrent droughts and water scarcity (see areas of cultivation in the section on study area). From 2001 to 2019 the mean growing season precipitation was flat for each of the years thereafter for maize, millet, and rice. To the best of our knowledge, the growing season precipitation assumed a flat state for these crops due to a reduction in the frequency of perturbations such as droughts and the occurrence of more stable growing season precipitation. However, though flat, this does not mean reliable as this often falls below the minimum threshold required to sustain crops and avoid droughts.

3.3. National Scale Maize, Millet and Rice Yield Vulnerability and Adaptive Capacity Indices

This study has found that of the three crops, rice has the highest vulnerability index of 0.77 (Figure 6) while maize has the second highest vulnerability index of 0.64 (Figure 6) and millet has the lowest of 0.5. This implies millet is the least vulnerable while rice is the most vulnerable of the three studied crops (Figure 6). This is consistent with the initial trends in the yields of these crops described above which shows that millet and maize are witnessing increasing yields while rice is declining. Also, millet has the highest R^2 followed by maize. The exposure and sensitivity indices are also consistent with the vulnerability index. In other words, when the vulnerability index is high, the exposure and sensitivity indices are also high. As can be seen on Figure 8 millet has the lowest exposure and sensitivity indices of 0.66 and 0.92 respectively while the exposure and sensitivity indices for maize and rice are much higher. Rice on the other hand also has the highest exposure and sensitivity indices among all three crops (Figure 6).
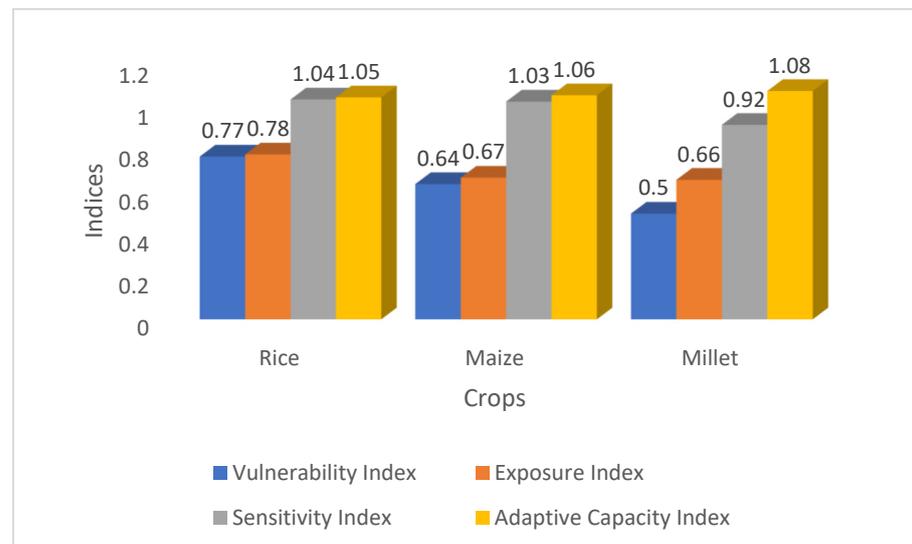
Figure 6. Simulated National Scale Exposure, Sensitivity, and Adaptive Capacity Indices.

In the context of the adaptive capacity index, this study has found that millet has the highest adaptive capacity index (1.08) followed by maize (1.06) while rice (1.05) has the lowest adaptive capacity index (Figure 6). Though the margin of difference between these indices is not very high, rice still stands out as the least adaptive of the three crops. The interesting observation here is that the crops with the highest adaptive capacity indices also have the lowest vulnerability, sensitivity, and exposure indices. An inverse indirect relationship exists between the adaptive capacity index and vulnerability, exposure, and sensitivity indices.

3.4. Sub-National Vulnerability Index Model Validation

The sub-national analyses were performed only for sites in which data were available; these sites coincide with the sites in which these crops are most dominantly cultivated.

Since maize grows in both the north and south of the country, this study looked at both southern and northern maize to establish a spatial variation. The results show that northern maize has the highest vulnerability index of about 1.21 while southern maize has a vulnerability index of 0.51 (Table 2). The higher vulnerability index of northern maize is linked to the fact that the north of the country witnesses recurrent and frequent droughts caused by declining precipitation from the south to north (Figure 7). On the other hand, southern maize has the highest adaptive capacity index of 1.06 while northern maize has the lowest adaptive capacity index of 0.94; this is consistent with the high vulnerability index (Table 2, Figure 7). In the context of maize, it can be said that the vulnerability increases from the south to the north. The second most vulnerable crop of the three is western highland rice with a vulnerability index of 0.78 and the second smallest adaptive capacity after northern maize of 1.02 (Table 2). The relatively high vulnerability index and low adaptive capacity index of western highland rice at the sub-national scale is consistent with the high vulnerability index recorded for rice at the national scale. Northern millet is the third most vulnerable crop after western highland rice with a vulnerability index of 0.52 (Table 2). These results show that if northern maize is left out, western highland rice will become the most vulnerable crop.

Table 2. Sub-national vulnerability indices at four sub-national sites.
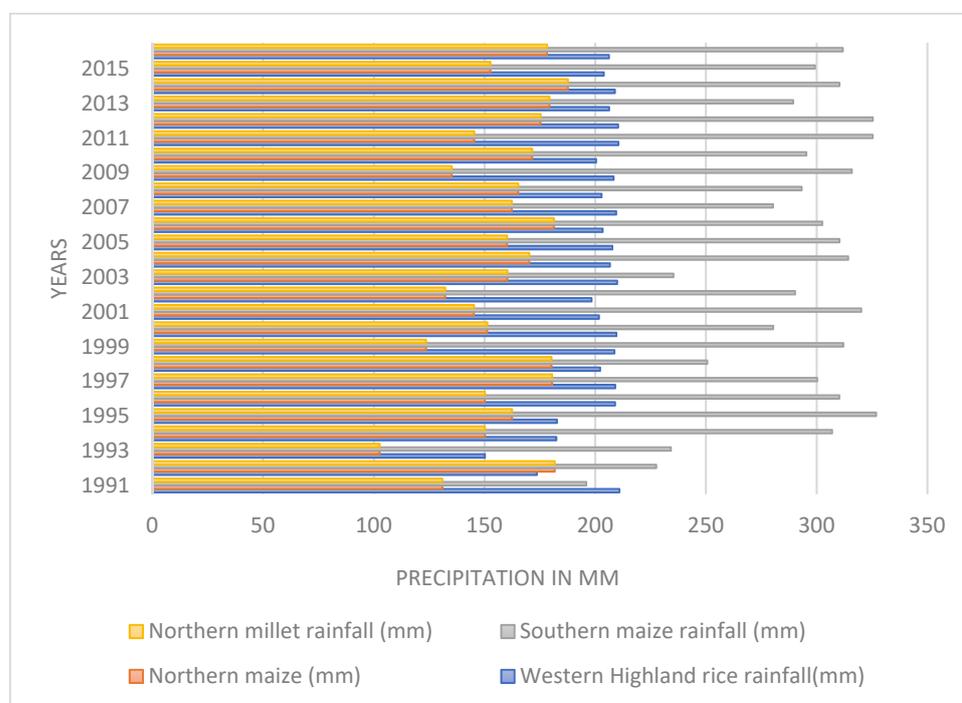
Sub-National Crops	Vulnerability Index	Exposure Index	Sensitivity Index	Adaptive Capacity Index
Southern Maize	0.51	0.55	1.02	1.06
Northern Maize	1.21	1.13	1.04	0.94
Western Highland Rice	0.78	0.76	1.04	1.02
Northern Millet	0.52	0.68	0.89	1.05
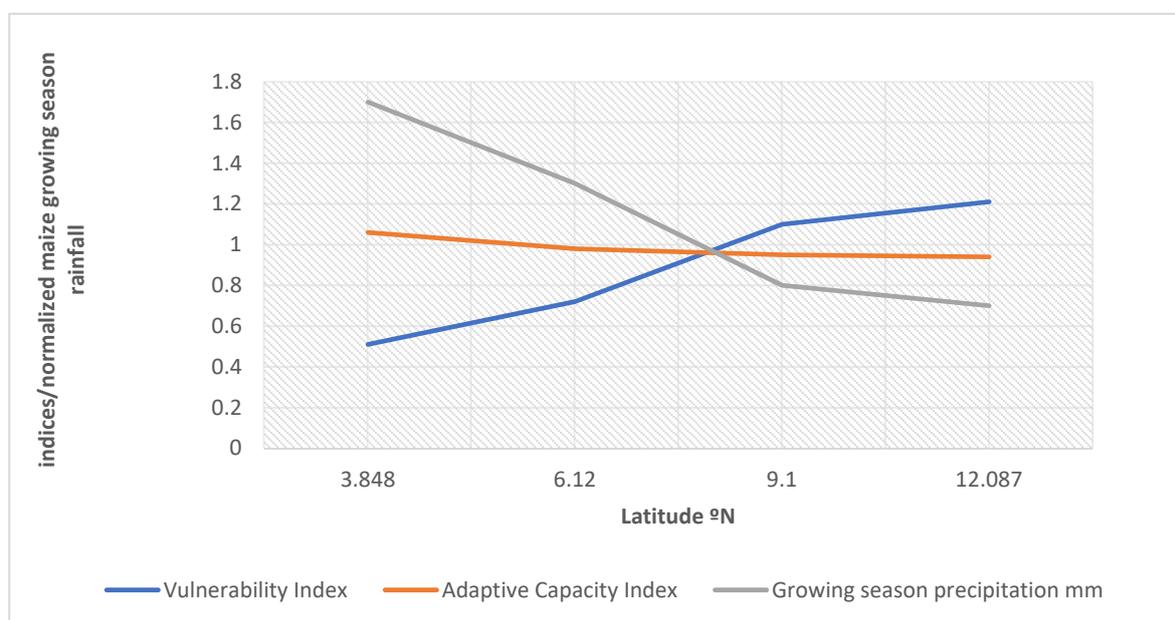
Figure 7. Latitudinal Variation in the Indices at the Sub-national Scale.

When the growing season precipitation is considered (Figure 8), it can be observed that southern maize has the highest growing season precipitation followed by western highland rice. Northern millet and northern maize have the same growing season, the reason why they both assume the same rates. It can be drawn from this figure that the growing season precipitation also declines from the south of the country to the north as northern millet and maize have the lowest growing season precipitation records. The records show that the

mean growing season precipitation for southern maize is about 300 mm annually while that for the western highland rice is about 200 mm annually (Figure 8). Northwards, northern maize, and millet record a mean growing season precipitation of about 150 mm annually. This confirms the hypothesis of declining precipitation northwards and therefore increased constraints on yields.

Figure 8. Sub-national Growing Season Precipitation Trends for Western Highland Rice, Southern maize, Northern maize, and millet.

4. Discussion

At the national scale rice has the highest vulnerability index and the lowest adaptive capacity index. However, the growing season precipitation for rice in Cameroon is relatively higher than the growing season precipitation for maize. Normally, it is expected that with a higher mean growing season precipitation than maize, rice should not be the most vulnerable crop; but this is not the case. This still however makes sense as it is important to consider that these crops all have different crop production seasons (see Figure 3) and are impacted by several other factors other than growing season precipitation. In addition, it is not only the mean annual growing season precipitation that is important in crop growth but rather growing season precipitation that is well distributed throughout the growing season of the crop. If the precipitation is concentrated at the beginning, middle or end of the season, then it is likely that crop growth might be affected negatively. In most cases, adequate growing season precipitation must be associated with moderate temperatures to ensure good harvest. Even at this rate, when there is adequate precipitation and temperature, crop failures might still occur if the soil is of poor quality, the planting species are not resistant to droughts or crop pests and the farmers do not have adequate access to organic and inorganic inputs. Therefore, as can be seen here crop vulnerability is a function of several variables and not just entirely climatic.

The declining rice yields in Cameroon that began around 1989 are consistent with the observations of previous studies. It has been argued that rice production in Cameroon was stable between 1960–1985. This period equally experienced spectacular evolution marked by increases in rice in terms of the relationship between yields and cultivated area. However, due to declining rice prices in the 1990s triggered by a decline in profitability, the economic crisis, and the devaluation of the local currency in 1994 the country tilted

from being self-sufficient in rice production to being a net importer of rice [53,56,57]. In fact, the production trends identified by [40] indicate an increase up to 1985 and a decline thereafter. This period of net decline in production was also consistent with the decline in support of irrigated rice production, a decline in fertilizers, pesticides and use of tractors. Furthermore, the fact that rice cultivation is in the hands of small-scale farmers (93%) who are ill equipped to meet the production challenges also comes to play. Consequently, in 2005, production was only able to supply 13% of Cameroonian rice consumption [57].

There is an inverse indirect relationship between vulnerability and adaptive capacity. This is also consistent with other studies across Africa. For example, the study conducted on the vulnerability of maize yields to droughts in Uganda in 2017 reported that there is a latitudinal variation in vulnerability with high levels of vulnerability of maize being linked to the higher latitudes in the north of the country while lower rates are observed in the south. At the same time, the study shows that the northern regions of Uganda have lower adaptive capacities when compared to the south of the country [5]. However, this current study has also observed the same trends with respect to southern and northern maize. Southern maize has a lower vulnerability index and a higher adaptive capacity index but in the north the vulnerability index of northern maize is higher while the adaptive capacity index is lower (Figure 8). In addition to variations in precipitation distribution during the maize growing season, other drivers of these variations are soil quality, and socio-economic status of the farmers involved in cultivating the crop [5]. Furthermore, another study that focused on the vulnerability of maize, cassava, beans, millet, groundnuts, and sweet potatoes agrees with the inverse indirect relationship between vulnerability and adaptive capacity. This study found cassava to be the most vulnerable crop at the national scale and maize the least vulnerable in Uganda [10]. Also, the fact that different crops are vulnerable across West-Central (Cameroon) to East Africa (Uganda), indicates that a movement from one ecological zone to another is associated with changes in levels of vulnerability as well as in the types of crops that are vulnerable due to differences in climate, soils, and other socio-economic conditions (Figure 7).

Policies to mitigate must aim at enhancing and revamping rice production in Cameroon. Much can be done through the introduction of high yielding varieties, drought and pests tolerant and resistant crop types, soils improvements and climate information management. Varieties of rice that do not have a well-developed aerenchymal are capable of sustaining rice yields while reducing emission of methane [55,58]. This is very important for rice production because the country depends a lot on rice imports and it is one of the most consumed crops in SSA and Cameroon [5,59]. It has been argued that since most of the rice cultivated in Cameroon is paddy rice, investments in modern irrigation infrastructure will go a long way to enhance production. In fact, Goufo, [59] argues that one of the main problems with rice production in Cameroon has to do with deteriorating irrigation infrastructure. To mitigate this effect, synergies between the government, farmers, NGOs, and other stakeholders must be put in place to install new and efficient irrigation facilities such as dams, canals, and drainage channels. However, this must be accompanied by improvements in access to agricultural production inputs such as fertilizers, pesticides, and tractors. All these efforts will be useless if the practice in which the Bororo herdsmen use the rice valleys for four months a year to feed their herds between March and November which is part of the crop growing season [59] is not controlled. Even though irrigation is said to enhance production, water management through mid-season drainage increases oxidation of soils and reduces methane emissions. However, water should only be reduced to a level that can be supported by the crops and this can be done daily [48,59]. Water levels should later be re-established to avoid prolonged water stress and consequent poor yields [59].

While the animals might eat the crops and damage them, this study is suggesting a mixed farming model in which the animals can be kept in different parts of the farms and fed with the rice straws from the paddy fields and the animal dung is used as fertilizers for the crops [55,58]. Organic materials like animal dung have the beneficial potential of

enhancing soil aeration and reducing methane emissions. Other additives like sulfates can also reduce the amount of methane emitted from paddy rice fields. Caution must be taken to ensure intermittent draining of the fields to reduce anerobic bacteria and thus methane missions which often increase with increasing flooding [59].

At the sub-national scale, northern maize has the highest vulnerability index and the lowest adaptive capacity index. This is consistent with the recurrent droughts and persistent declines in precipitation from the south to the north. On the other hand, the fact that southern maize has the lowest vulnerability index is explained by the wetter nature of the area that contrasts with the north of the country. These finding show that different crops are vulnerable at the national and subnational scale. This is important to underscore because what is obtained at the national scale might not be reflected at the sub-national scale as different regions are differentially affected by different precipitation characteristics, temperatures, soils, access to farm inputs, high yielding varieties and crop pests [6,48,59,60]. Therefore, just like with national scale rice, northern maize will benefit from a combination of irrigation and farm inputs in the context of organic fertilizers and enhanced farmer access to climate related crop planting information to better guide farming decisions. Looking at the water requirements for these three crops, the FAO [61] reports that millet has a water requirement of 450–65 mm/total growing period, maize has a water requirement of 500–800 mm/total growing period and rice a water demand of 90–150 mm/total growing period. At the national scale, rice is the most vulnerable crop, yet its water requirements are the lowest of all the three. As mentioned earlier, this shows that water requirements in essentially rainfed agriculture are not the only determinants of yield. Sub-nationally, maize is the most vulnerable crop and at the same time has the highest water requirement of all three crops. Being that the sub-national observations are site specific and represent the realities of the local environment, the persistent drought especially in the north of the country are likely to impact the yield of maize more than most other crops.

5. Conclusions

At the national scale and for the three crops under study, millet has the lowest vulnerability index while rice has the highest vulnerability index. Sub-nationally, northern maize is the most vulnerable crop, followed by western highland rice. There is an indirect inverse relationship between vulnerability and adaptive capacity at both scales of analysis. For example, millet with the lowest vulnerability index nationally has the highest adaptive capacity index. From a policy and farming livelihood perspective, this study suggests the modernization of Cameroon's irrigation infrastructure, use of mixed farming, farm input, soil additives, economic viability and intermittent/mid-season draining to reduce the vulnerability of rice.

It should however be cautioned that, the adaptive capacity index used here is based on proxies such as literacy and poverty rates due to the difficulty associated with assessing adaptive capacity. Also, it is important to note that the time series data for the national scale analysis spans from 1961 to 2019 while that for the sub-national scale spans 1991–2016; though relatively long, more data beyond 1991 and 2016 would have better optimized the sub-national scale simulations. In addition, the absence of sufficient sub-national scale yield data repositories for the three crops involved has greatly limited the exploration at that scale. However, with the availability of time series yield data for some areas, this work has attempted to validate the vulnerability index. Finally, this study fails to compare how other approaches of simulating vulnerability simulate this data with respect to our current index. Despite these weaknesses, this study has for the first time in Cameroon provided a holistic approach by introducing the three components of vulnerability and by integrating precipitation and socio-economic variables. With this achieved, it is still important for research to be carried out on the vulnerability of other crops, verifications of future scenarios as well as crop yield gaps in Cameroon, and the introduction of more sites in the sub-national scale analysis as data becomes available. Also, it is important to note that in addition to climatic drivers, crop yields are often influenced by a complex combination

of variables such as precipitation, temperatures, soils, fertilizers, high yielding varieties, crop pests and diseases as well as the socio-economic conditions of the farmers involved. Therefore, this study provides a snapshot of the role of growing season precipitation and socio-economic drivers in influencing the vulnerability of the concerned crops.

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