Accepted Manuscript

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PII: S0921-8181(17)30322-3
DOI: <https://doi.org/10.1016/j.gloplacha.2018.01.011>
Reference: GLOBAL 2720
To appear in: *Global and Planetary Change*
Received date: 18 June 2017
Revised date: 14 December 2017
Accepted date: 10 January 2018

Please cite this article as: Bahareh Kamali, Karim C. Abbaspour, Bernhard Wehrli, Hong Yang , Drought vulnerability assessment of maize in Sub-Saharan Africa: Insights from physical and social perspectives. The address for the corresponding author was captured as affiliation for all authors. Please check if appropriate. Global(2017), <https://doi.org/10.1016/j.gloplacha.2018.01.011>

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Drought vulnerability assessment of maize in Sub-Saharan Africa: insights from physical and social perspectives

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Abstract

Drought as a slow-onset phenomenon inflicts important losses to agriculture where the degree of vulnerability depends not only on physical variables such as precipitation and temperature, but also on societal preparedness. While the scopes of physical and social vulnerability are very different in nature, studies distinguishing these two aspects have been lacking. In this study we address the physical and social aspects of drought vulnerability of maize ($CDVI_{phy}$ and $CDVI_{soc}$) in Sub-Saharan Africa (SSA). To quantify vulnerability, we applied a probabilistic framework combining a Drought Exposure Index (DEI) with a physical or social Crop Failure Index, CFI_{phy} or CFI_{soc} , respectively. DEI was derived from the exceedance probability of precipitation. Maize yields, simulated using the Environmental Policy Integrated Climate (EPIC) model, were used to build CFI_{phy} , whereas the residual of simulated and FAO recorded yields were used to construct CFI_{soc} . The results showed that southern and partially central Africa are more vulnerable to physical drought as compared to other regions. Central and western Africa, however, are socially highly vulnerable. Comparison of $CDVI_{phy}$ and $CDVI_{soc}$ revealed that societal factors cause more vulnerability than physical variables in almost all SSA countries except Nigeria and South Africa.. We conclude that quantification of both drought vulnerabilities help a better characterization of droughts and identify regions where more investments in drought preparedness are required.

Keywords:

EPIC model, Probability framework, Crop Failure Index, Drought Exposure Index, exceedance probability.

1. Introduction

Crops exhibit known responses to climate variability (Challinor et al., 2009). Crop models can predict the vulnerability of food production to drought (Fraser et al., 2013). However, drought vulnerability is a complex, context-specific concept (Naumann et al., 2014) and its definition has evolved over time. According to the IPCC (Intergovernmental Panel on Climate Change) Fourth Assessment Report, vulnerability is defined as the degree to which an environmental or a social system is exposed to adverse effects of climate change and is a function of exposure, sensitivity, and adaptive capacity (IPCC, 2007; Nelson et al., 2007; Parry et al., 2007). The IPCC Fifth Assessment Report emphasizes on the social aspect of drought vulnerability (IPCC, 2013).

From the agricultural point of view, although the direct impact of precipitation shortfall is crop yield reduction, the underlying cause of this vulnerability to meteorological drought can be beyond the natural scope (Naumann et al., 2014). Generally speaking, “physical vulnerability” induces yield loss only due to water stress during crop growth, but reduced production in a drought event has multiple factors. Stressors making one region vulnerable may be different for another region and are highly dependent on the degree of development and socioeconomic status of a particular community (Antwi-Agyei et al., 2012). Reasons like political, economic, and social conditions significantly exacerbate drought impacts especially in developing countries (Bashir and Schilizzi, 2013; O'Brien et al., 2004). Turner and Dumas (2013) found that in many cases social factors dominate. These assessments indicate that climate change can affect crop production well beyond the physical drought stresses.

Given its complexity, many studies have conducted vulnerability quantification at different levels, from developing qualitative methods (Derbile, 2013; Fussel and Klein, 2006; Luers et al., 2003), to building and validating composite indicators (Carrão et al., 2016; Naumann et al., 2014; O'Brien et al., 2004), and to identifying factors influencing vulnerability (Antwi-Agyei et al., 2012; Bryan et al., 2009; Malcomb et al., 2014). The results show that some regions are at a higher risk of severe or even total crop production loss (Muller et al., 2011; Roudier et al., 2011) for a relatively mild drought. In countries of Sub-Saharan Africa (SSA), poverty limits installing adaptation measures to drought (Masih et al., 2014; Shi and Tao, 2014); therefore, the physical and social vulnerability to drought can be very different. However, few studies on drought vulnerability have measured the difference

between physical and social drought vulnerability or highlighted their relative importance (Terence et al., 2017; Zarafshani et al., 2012). Therefore, there is a need to develop methods that quantify both aspects of drought vulnerability simultaneously. Such a level of understanding is important to propose effective adaptation measures to drought and to enhance the resilience of agricultural production (Cooper et al., 2008).

This study bridges the existing gap in quantification of the two aspects of drought vulnerability for maize in SSA. A process-based EPIC crop model is used to simulate maize yields to derive information on crop's physical response to climate variability (Iglesias et al., 2012; Lobell and Burke, 2010). The reported yields by FAO reflect the impacts of both physical and social factors. We quantify maize drought vulnerability by incorporating drought exposure and crop failure indices in a probability framework. The regions that are physically and socially highly vulnerable are identified and implications of the two aspects of drought vulnerability are discussed.

SSA was chosen as the study area because it is the home to one billion people (World Bank, 2016) frequently struck by droughts. Rainfall has large spatial and temporal variability in the region with significant impact on food production and livelihoods of the people (Hellmuth et al., 2007). The recurrence of droughts in the past decades has triggered many famines, resulting in the death of millions of people and food insecurity across the sub-continent. The expected adverse impacts of climate change on crop production in SSA add further risk to the future food security of the region (Liu et al., 2008; Muller, 2011; Roudier et al., 2011; Schlenker and Lobell, 2010).

Methodology

2.1. Simulation and calibration of maize yield using EPIC⁺

Crop yield was simulated using EPIC⁺ which is an extended version of EPIC coupled with the Sequential Uncertainty Fitting (SUFI-2) algorithm for calibration (Kamali et al., 2018). EPIC is a bio-physical agronomic model developed in the mid-1980s (Williams et al., 1989). The crop growth module of EPIC estimates crop yield by multiplying the above ground biomass at maturity with a water stress adjusted harvest index (Williams et al., 1989). The model operates on a daily basis and takes into account all relevant processes of soil–crop–atmosphere system, climate data, management

data such as a leaf area index, a crop parameter for converting energy to biomass, and fertilizer deficiencies (Williams et al., 1989). Validation studies with EPIC applications on different scales have demonstrated satisfactory results in previous works (Causarano et al., 2008; Gaiser et al., 2010; Liu et al., 2013; Wang et al., 2012).

EPIC is originally a field-scale model. In EPIC⁺ as a spatially explicit model, the EPIC application is extended to larger scales using a Python framework following the work by Kamali et al. (2018). The framework divides the region of study into a numbers of grids based on a specified resolution (here 0.5°) and executes EPIC on each grid cell. The site-specific input data included longitude, latitude, slope, elevation (DEM), climate, soil, crop calendar, fertilizer, and soil (Table 1). All input data were converted into 0.5° resolution.

Table 1 Summary of the input data and the sources used for simulating maize in SSA. All data were transformed into a 0.5°x0.5° resolution (Kamali et al., 2018).

Input data	Description	Resolution	Year	Source
DEM, Slope	Digital elevation model GTOPO30	1 km (5"x5")	Edition 2004	U.S. Geological Survey (2004)
A_{RF}	Rainfed cultivated area	10 km (5'x5')	2000	MIRCA2000 ¹ version 1.1 (Portmann et al., 2010)
Climate	Daily maximum and minimum temperature, precipitation, solar radiation, relative humidity, wind speed, CO ₂ concentration	50 km (0.5°x0.5°)	1970-2012	WFDEI ² meteorological forcing data (Weedon et al., 2011)
Soil	Soil map and database	10 km (5'x5')	2006	ISRIC-WISE ³ (Batjes, 2006)
Planting & harvesting dates	Based on temperature linked to crop calendar	50 km (0.5°x0.5°)	1990s to early 2000s	SAGE ⁴ (Sacks et al., 2010)
Fertilizer	Fertilizer use	National	2002	FertiStat (FAO, 2007)

¹ Monthly Irrigated and Rainfed Crop Areas

² WATCH-Forcing-Data-ERA-Interim

³ International Soil Reference and Information Centre-World Inventory of Soil Emission Potentials

⁴ Center for Sustainability and the Global Environment

In the developed framework, EPIC⁺ is equipped with the SUFI-2 algorithm for automatic calibration (Abbaspour et al., 2004). The SUFI-2 algorithm maps all uncertainties in the output on the parameter ranges. The uncertainty is quantified by the 95% prediction uncertainty (95PPU) calculated

at the 2.5% and 97.5% levels of cumulative distribution of an output variable obtained through the Latin Hypercube Sampling in the parameters space. Two criteria, *r-factor* and *p-factor*, judge the goodness-of-fit and the level of uncertainty of the model. The *p-factor* criterion represents the fraction of measured data bracketed by the 95PPU uncertainty band and varies from 0 to 1, where 1 means 100% of the measured data are bracketed by the model simulation (expressed as the 95PPU). Values around 0.5 are usually acceptable for crop simulation (Abbaspour et al., 2015). The *r-factor* criterion is the average width of the 95PPU band divided by the standard deviation of the measured variable, which is a measure of the prediction uncertainty. The ideal value for *r-factor* is 0, with an acceptable practical value of around 2 for crop yield.

The *Standardized Root Mean Square Error (RSR)* criterion proposed by Singh et al. (2004) was selected as the objective function in the SUFI-2 algorithm to compare the performance of country level simulated yield (Y_{sim}) with national level FAO yield (Y_{obs}) (FAO, 2012) as:

$$RSR = \frac{RMSE}{STDEV_{obs}} = \frac{\sqrt{\sum_{t=1}^{33} (Y_{obs,t} - Y_{sim,t})^2}}{\sqrt{\sum_{t=1}^{33} (Y_{obs,t} - \bar{Y}_{obs})^2}} \quad (1)$$

Y_{sim} was obtained from simulating irrigated (Y_{IR}) and rainfed (Y_{RF}) yields in EPIC on n grids within a country and is then aggregated to country level using weighted areal averages as (Folberth et al., 2012):

$$Y_{sim} = \frac{\sum_{i=1}^n Y_{RF,i} \times A_{RF,i} + Y_{IR,i} \times A_{IR,i}}{\sum_{i=1}^n A_{RF,i} + A_{IR,i}} \quad (2)$$

where A_{IR} and A_{RF} are respectively irrigated and rainfed cultivated areas in each grid.

We simulated maize for the years 1970-2012. Considering the first 10 years as equilibrating period for soil moisture and nitrogen initial conditions, we calibrated the model for the period 1980-2012. Model calibration was implemented in three steps (Kamali et al., 2018). In the first step, planting dates at grid level were adjusted in 50 simulations and their values were fixed. In the next step, parameters related to agricultural operations including potential heat unit, planting density and

different fertilization application rates (Nitrogen, Phosphorous, and Potassium) were calibrated. The best values were used as fixed values for the next step. Finally and in the last step, six Crop parameters (Biomass-energy ratio, Harvest index, Optimal temperature for plant growth, Minimum temperature for plant growth, Lower limit of harvest index, Fraction of water in crop yield) and two Model parameters (Water stress harvest index and SCS curve number index) highlighted as the most sensitive parameters in literature were calibrated (Wang et al., 2012; Xiong et al., 2014). More details on the initial ranges of parameters are found in Kamali et al. (2018).

2.2. Conceptualizing crop drought vulnerability

Crop Drought Vulnerability Index (*CDVI*) was built with the Drought Exposure Index (*DEI*) as a measure of the degree of stresses on the system; and the Crop Failure Index (*CFI*) as the response of the system to the stress.

2.2.1. Definition of Drought Exposure Index (*DEI*)

DEI is derived from the Standardized Precipitation Index (*SPI*) (McKee et al., 1993). *SPI* is calculated first by fitting a two-parameters gamma distribution function to precipitation (*PCP*). Once the probability distribution function is determined, the Cumulative Distribution Function (CDF_{PCP}) is calculated and the inverse normal function is applied to obtain *SPI*. This means that *SPI* and its associated CDF_{PCP} can be converted to each other. We define *DEI* by using CDF_{PCP} , which was described by a two-parameters gamma distribution (Bordi et al., 2001a; Lloyd-Hughes and Saunders, 2002):

$$DEI = 1 - CDF_{PCP} \quad (3)$$

We tested the performance of normal, log-normal and two-parameter gamma distribution functions using the Kolmogorov-Smirnov (K-S) statistic test for the precipitation data. The results showed that all the three distributions show a good fit for all months and less than 5% of grid cells

failed the test (Fig. S1). The average p -values were slightly higher for the gamma distribution. A two-parameter gamma distribution was used. Other studies confirmed the suitability of gamma distribution function (Bordi et al., 2001b; Lloyd-Hughes and Saunders, 2002).

DEI varies between 0 and 1 with $DEI > 0.5$ indicating drought situations and $DEI < 0.5$ being equivalent to non-drought. Fig. 1a presents the schematic representation of transforming PCP to CDF_{PCP} (left), and CDF_{PCP} to DEI (right). $DEI-X$ is defined over different time scales ($X = 1, 3, 6, 9$, and 12-month(s)). $DEI-X$ at each month is obtained from total precipitation over the last X months. For example, $DEI-3$ at the end of February compares the December–January–February precipitation totals in that particular year with the December–January–February precipitation totals of all other years. We also defined five categories within the ranges of CDF_{PCP} and DEI as: wet, near normal, mild to moderate drought, severe to extreme drought, and exceptional drought (Svoboda et al., 2002) (Table 2).

Table 2

Five categories of cumulative distribution functions (CDF_{PCP} , $CDF_{Y_{sim}}$, $CDF_{Y_{obs}-Y_{sim}}$) and their equivalent Drought Exposure (DEI) and Crop Failure Indices (CFI).

Category	CDF_{PCP} , $CDF_{Y_{sim}}$, $CDF_{Y_{obs}-Y_{sim}}$	DEI , CFI
Wet	0.692 to 1.00	0.00 to 0.308
Near normal	0.308 to 0.692	0.0308 to 0.692
Mild to moderate	0.115 to 0.308	0.692 to 0.885
Severe to extreme	0.023 to 0.115	0.885 to 0.115
Exceptional	0.00 or 0.0230	0.977 to 1.00

Fig. 1. Schematic representation of transforming a) precipitation from its cumulative distribution function (CDF_{PCP}) to the Drought Exposure Index (DEI); b) simulated maize yield (Y_{sim}) from its cumulative distribution function ($CDF_{Y_{sim}}$) to the physical Crop Failure Index (CFI_{phy}); and c) the residual of simulated and observed yields from its cumulative distribution function ($CDF_{Y_{obs}-Y_{sim}}$) to the socioeconomic Crop Failure Index (CFI_{soc}).

2.2.2. Definitions of the physical and social Crop Failure Indices (CFI_{phy} and CFI_{soc})

The physical Crop Failure Index (CFI_{phy}) considers only climatic influences and its computation is based on Y_{sim} obtained from the calibrated EPIC, which is not influenced by social factors as (Fig. 1b):

$$CFI_{phy} = 1 - CDF_{Y_{sim}} \quad (4)$$

According to this definition, crop failure occurs in years when CFI is larger than 0.5.

CFI_{soc} integrates the non-physical influence of drought on crop loss. It is important to point out that we do not aim to consider details of socioeconomic factors influencing crop failure; but only imply that Y_{obs} is based on a combination of social and physical factors, while Y_{sim} merely considers the physical factors. Therefore, we use the residuals of Y_{obs} and Y_{sim} ($Y_{obs}-Y_{sim}$) to represent crop losses due to socioeconomic factors and quantify it by CFI_{soc} as:

$$CFI_{soc} = 1 - CDF_{Y_{obs}-Y_{sim}} \quad (5)$$

According to the above definition, crop failure occurs when Y_{obs} is smaller than Y_{sim} . A normal distribution function with 0 mean is used for the residual of observed and simulated maize yields. Positive residuals mean that the region is able to produce more crop than expected, considering the climate influence; whereas negative residuals indicate that the region did not adapt to climate stresses (Fig. 1c). The five categories defined in Table 2 for DEI remain valid for CFI_{phy} and CFI_{soc} .

2.2.3. Drought vulnerability definition based on incorporating DEI and CFI

The vulnerability of a system is defined as the ability to respond to variables of exposure. As the degree of exposure and the capacity to withstand them are uncertain, vulnerability is quantified probabilistically (Foti et al., 2014). Physical ($CDVI_{phy}$) and social vulnerabilities ($CDVI_{soc}$) are defined as the probabilities that CFI_{phy} and CFI_{soc} , respectively, are larger than DEI (Foti et al., 2014); that is:

$$\begin{aligned} CDVI_{phy} &= Pr[DEI < CFI_{phy}] = Pr [DEI - CFI_{phy} < 0] \\ CDVI_{soc} &= Pr[DEI < CFI_{soc}] = Pr [DEI - CFI_{soc} < 0] \end{aligned} \quad (6)$$

From probabilistic points of view, vulnerability depends on the mean, variance, and covariance of DEI , CFI_{phy} , or CFI_{soc} . Assuming $Z_{phy} = DEI - CFI_{phy}$ and $Z_{soc} = DEI - CFI_{soc}$ and in the case of non-Gaussian Z_{phy} and Z_{soc} , the above equations are written:

$$\begin{aligned} CDVI_{phy} &= \frac{1}{2} + \frac{1}{2} erf \left[\frac{(-\mu_{DEI} + \mu_{CFI_{phy}})}{\sqrt{2\sigma_{Z_{phy}}^2}} \right] \\ CDVI_{soc} &= \frac{1}{2} + \frac{1}{2} erf \left[\frac{(-\mu_{DEI} + \mu_{CFI_{soc}})}{\sqrt{2\sigma_{Z_{soc}}^2}} \right] \end{aligned} \quad (7)$$

where $erf()$ is the Gaussian error function, μ_{DEI} is the mean of DEI . More details on the derivation of above equations, their components and their influence on vulnerability are provided in Supplementary material.

3. Results

3.1. Calibration performance of EPIC

The results of simulated maize given in terms of RSR before and after calibration (Table 3) indicated significant improvement in model performance after calibration. The RSR values for all countries except Democratic Republic of the Congo, decreased to around 1 or less. The RSR value for Democratic Republic of the Congo decreased significantly from 45.9 to 6.27. The main reason for high RSR in this country is a reported constant yield of 0.8 t ha^{-1} for the whole 33-year period which does not seem to be realistic. Comparison of the average of simulated and observed yields during 1980-2012 shows that the differences are smaller than 0.1 t ha^{-1} in most countries suggesting satisfactory performance of the EPIC⁺ in simulating crop yields.

Table 3. Country level results of the EPIC calibration with the SUFI-2 algorithm based on *RSR* before calibration, *RSR* after calibration, *p-factor* and *r-factor* criteria ($\bar{Y}_{obs}$ is the average observed maize yield and $\bar{Y}_{sim}$ is the average simulated yield) obtained from the work by Kamali et al. (2018).

	Country	$\bar{Y}_{obs}$	$\bar{Y}_{sim}$	<i>RSR</i>	<i>p-factor</i>	<i>r-factor</i>
Eastern Africa	Burundi	1.17	1.17	1.38	0.55	1.80
	Comoros	2.20	2.13	1.13	0.42	1.95
	Eritrea	0.63	0.39	1.45	0.58	1.98
	Ethiopia	1.78	1.80	0.91	0.52	1.81
	Kenya	1.67	1.69	0.86	0.61	1.74
	Madagascar	1.14	1.37	1.42	0.79	2.54
	Malawi	1.34	1.37	0.94	0.45	2.25
	Mozambique	0.68	0.64	1.12	0.61	1.56
	Rwanda	1.23	1.18	1.08	0.43	1.04
	Somalia	0.89	0.80	1.22	0.42	1.08
	Sudan	0.79	0.72	1.33	0.48	1.05
	Tanzania	1.48	1.10	1.20	0.58	0.94
	Uganda	1.59	1.62	0.85	0.58	2.48
	Zambia	1.85	1.86	0.89	0.45	1.31
	Zimbabwe	1.16	1.17	1.12	0.37	1.67
Central Africa	Angola	0.52	0.55	0.99	0.88	2.38
	Cameroon	1.81	1.79	1.00	0.48	1.38
	Central African Republic	0.94	1.05	1.16	0.49	0.74
	Chad	0.94	0.94	0.84	0.66	2.05
	Democratic Republic of the Congo	0.80	0.81	6.27	0.48	1.05
	Gabon	1.56	1.49	1.35	0.70	1.95
	Republic of Congo	0.76	0.75	2.16	0.88	2.39
Southern Africa	Botswana	0.29	0.30	1.39	0.52	2.33
	Lesotho	0.80	0.72	1.27	0.42	2.45
	Namibia	1.36	1.12	1.02	0.42	1.23
	South Africa	2.67	2.48	0.92	0.55	0.79
	Swaziland	1.35	1.39	1.06	0.42	1.49
Western Africa	Benin	1.03	1.08	0.99	0.70	1.83
	Burkina Faso	1.34	1.32	0.97	0.52	1.07
	Djibouti	1.80	1.84	1.20	0.70	2.73
	Gambia	1.30	1.29	0.93	0.82	2.97
	Ghana	1.37	1.46	1.07	0.52	1.14
	Guinea	1.23	1.27	1.96	0.45	2.02
	Ivory coast	1.51	1.73	1.08	0.48	1.44
	Mali	1.50	1.70	0.98	0.55	1.55
	Mauritania	0.70	0.67	1.18	0.61	2.25
	Niger	0.69	0.68	0.85	0.70	1.88
	Nigeria	1.44	1.39	0.98	0.70	1.84
	Sierra Leone	0.99	1.00	1.09	0.53	2.07
	Senegal	1.29	1.27	0.92	0.86	2.44
	Togo	1.08	1.19	1.26	0.52	1.18

The p -factors with values around 0.5 or more in all countries indicate that over 50% of data were bracketed with the 95PPU band which are satisfactory for crop calibration during the 33 years of time span (Table 3). The r -factor values as the representative of the width of the 95PPU band are smaller than 2.5 and in most countries smaller than 2 which are acceptable for yield simulation.

3.2. Spatiotemporal pattern of DEI and CFI_{phy}

To identify the most relevant time scale of DEI for vulnerability analysis, the correlation coefficients between DEI -1, 3, 6, 9, and 12 during growing seasons and CFI_{phy} were calculated. The results showed higher correlation in southern and eastern Africa as well as Sahelian strip countries (mostly larger than 0.5) as compared to central Africa and southern regions of the Sahelian strip where the values ranged between 0.2 and 0.5 (Fig. 2a-e). The lower correlation coefficient values in central Africa and countries along the west coast of western Africa are mostly related to high precipitation (larger than 1200 mm yr⁻¹), which indicates that crop losses there are not correlated to water stress. DEI -12 was least correlated with CFI_{phy} , especially in most countries, indicating that longer exposure times are not adequate for agricultural loss assessment. DEI -3 and DEI -6 with the highest correlation coefficients in most cases were identified as the most representative time scales (Fig. 2 c, b).

Fig. 2. Correlation coefficients between different time scales of Drought Exposure Index (DEI) (DEI -1, 3, 6, 9, 12) and physical Crop Failure Index (CFI_{phy}) for maize.

For each grid, we selected the time scale with the highest correlation for subsequent analysis of vulnerability. The grid level *DEI* between 1980 and 2012 indicates that SSA experienced many severe to extreme drought periods (Fig. 3). Between 1982 and 1984, almost all countries experienced drought situations. The southern and western Africa experienced severe to extreme drought in 1987. Later, and between 1992 and 1995, central and southern African countries experienced severe and extreme drought situations. Between 1999 and 2012, less drought exposure was evident. However, southern and central Africa experienced the least wet period and rainfall were mostly in the near normal situation during the last decades. Yearly *CFI_{phy}* patterns (Fig. 4) were approximately similar to the *DEI* patterns in Fig. 3 for some regions whereas were different in others. The drought period 1982-1984 significantly influenced southern and eastern Africa with severe to extreme intensity, whereas the central African countries were least exposed to high *CFI_{phy}* and were mostly in the near normal situations (Fig. 4). This clearly shows that drought periods identified by *DEI* did not reflect with the same intensity in *CFI_{phy}*.

Fig. 3. The grid level pattern of the annual Drought Exposure Index (*DEI*) during 1980 and 2012.

Fig. 4. The grid level patterns of the annual physical Crop Failure Index (CFI_{phy}) during 1980 and 2012.

3.3. Physical and social crop drought vulnerability

The $CDVI_{phy}$ and $CDVI_{soc}$ calculated in this study (Eq. S4) quantifies vulnerability based on the interactions of $DEIs$ and CFI for the 33 years of studied period and does not differentiate periods with high vulnerability from low ones. The $CDVI_{phy}$ distribution shows values larger than 0.46 in most SSA countries indicating that maize yield is vulnerable to climate variability (Fig. 5a). Botswana, Zimbabwe, partially Mauritania, western part of South Africa, and central Tanzania with $CDVI_{phy}$ larger than 0.57 were identified as the most physically vulnerable regions. Namibia, western Angola, north part of Central African Republic, and partially Democratic Republic of Congo with $CDVI_{phy}$ between 0.52 and 0.57 were placed in second vulnerable regions (Fig. 5a).

Fig. 5. Spatial distribution of a) grid level physical maize drought vulnerability ($CDVI_{phy}$); b) country level social maize drought vulnerability ($CDVI_{soc}$); and c) the residual of $CDVI_{phy}$ and $CDVI_{soc}$. The results are based on the average vulnerability of 33-years.

The average $CDVI_{soc}$ calculated at the country level showed a very different picture from $CDVI_{phy}$. Overall, western and central African countries, Ethiopia, Zimbabwe, and Namibia were socially most vulnerable ($CDVI_{soc} > 0.52$) compared with eastern Africa, South Africa, Sudan, and Chad. Nigeria and Somalia were least vulnerable as the $CDVI_{soc}$ was smaller than 0.46 (Fig. 5b). Although, Zimbabwe exhibited the highest degree of $CDVI_{phy}$ and $CDVI_{soc}$, the same was not true for countries like Madagascar, Mali, Benin, Burkina Faso, and Ivory Coast, where the degree of $CDVI_{phy}$ was not as high as $CDVI_{soc}$ (Fig. 5 a,b). The $CDVI_{phy}$ and $CDVI_{soc}$ values in Zimbabwe indicated that both climatic and social factors are the limiting factors for maize production in this country (Fig. 5b). However, in other countries there was a large difference between $CDVI_{phy}$ and $CDVI_{soc}$, indicating a weak adaptive capacity of these countries to drought.

Due to lack of observed yields at grid level, we could calculate $CDVI_{soc}$ only at country level. To compare the two vulnerability types at grid level, we assigned the calculated country level values of $CDVI_{soc}$ to all grids within the country. The grid level residuals between two types of vulnerability i.e. $CDVI_{phy} - CDVI_{soc}$ was calculated at grid level (Fig. 5c). In most countries, $CDVI_{soc}$ was larger than $CDVI_{phy}$ meaning that social vulnerability is more critical for the region than the physical one. The residuals exceeded 0.1 in countries like Ivory Coast, Benin, Mali, Zimbabwe, and Madagascar. In contrast, South Africa, Botswana, and Nigeria with a lower degree of $CDVI_{soc}$ were identified as drought-resilient countries.

We also compared the country level $CDVI_{soc}$ with median, 25th and 75th percentiles of $CDVI_{phy}$ calculated at grid level (Fig. 6). The results showed that $CDVI_{soc}$ was larger than 75th percentiles of $CDVI_{phy}$ in most countries (Fig. 6) indicating that in most parts of a country, $CDVI_{soc}$ is larger than $CDVI_{phy}$. Mauritania and Mali from western Africa, southern African countries, Gabon and Republic of Congo from central Africa showed large variability in $CDVI_{phy}$, meaning that the degree of vulnerability is spatially different and therefore various adaptation strategies might be required depending on the residual between physical and social vulnerability. In Tanzania, for example, $CDVI_{soc}$ equals median of $CDVI_{phy}$, however over 50% of area are socially more vulnerable.

Fig. 6. Country level comparison of the physical cumulative drought vulnerability indices $CDVI_{phy}$ (boxplot) and social indices $CDVI_{soc}$ (red points). The boxplots show the 25th and 75th percentiles of the spatial variability of $CDVI_{phy}$ from grids within a country.

4. Discussion and conclusion

4.1. The effectiveness of proposed methodology for quantifying $CDVI_{soc}$ and $CDVI_{phy}$

This study demonstrated a method to distinguish and quantify physical and social crop drought vulnerability based on a quantitative assessment of DEI and CFI . Our analysis represents an important step forward in the current agricultural drought vulnerability assessment. Such level of understanding is particularly significant in SSA due to intrinsic climatic variability, reliance on rainfed agriculture as well as lack of coping infrastructure and resources of the society.

We applied a probabilistic methodology to define vulnerability and its components (DEI , CFI , $CDVI$). Integrating the probabilistic concept supports a more reliable inference of the likelihood and relevance of each index. Besides, it allows for explicit inclusion of thresholds, as all indices are transformed to the same range from 0 to 1 with five classes (Table 2). Using standardized definitions of DEI and CFI , one can normalize the degrees of severity for each single value, which facilitates the comparison on different spatial resolutions or with other available standardized indices in literature.

We inferred that the residual of the simulated and observed yields reflects the socio-economic indicator of vulnerability because the application of EPIC did not consider man-made effects such as developments in the agricultural machinery and technology. However, a certain degree of uncertainties associated with model simulation which might slightly influence our analysis. We accounted for

model uncertainty by linking SUFI-2 to EPIC (details previously mentioned in Kamali et al. (2018)). The uncertainty in the observed yield, however, was more difficult to address and requires more details at smaller spatial scales. To partially account for it, we only took those observed yields, which were outside the 95% prediction uncertainty (95PPU) band of the simulated yields. The residual between Y_{obs} and Y_{sim} was also used in previous works as a criteria to distinguish regions that are resilient and sensitive to drought (Bryan et al., 2015).

Moreover, the magnitude of socioeconomic factors is substantially larger in most of countries. Comparing Y_{obs} with Y_{sim} in countries such as Burkina Faso, Ghana, Ivory coast, and Nigeria (Fig. S2), one can see significant agreement between the average of simulated and observed yields (Table 3). However, the existing trend in observed yields cannot be related to modeling uncertainty, but stems from socioeconomic factors. It is clear that model uncertainty does not follow a trend (Fig. S2). Therefore, not surprisingly, social vulnerability maps revealed clear differences between countries with a relatively strong economy such as Nigeria and South Africa, and Tanzania with other countries like Zambia and Ivory Coast where rather poor social adaptive capacity exacerbated vulnerability.

4.2. Implications of $CDVI_{phy}$ and $CDVI_{soc}$ for SSA countries

We found that $CDVI_{soc}$ was higher than $CDVI_{phy}$ for most countries revealing that there is a significant potential to increase maize yield by designing adaptation strategies and farmer-managed agricultural interventions. Using our vulnerability maps, one can identify promising hotspots for drought adaptation investment. Despite different initial assumptions, our results show some consistency with the findings of HarvestChoice (2013), where normalized potential maize yields were compared against actual yield. Their analysis also highlighted South Africa, Lesotho, and Tanzania as countries with high-level productivity despite low level of inherent potential yields. By contrast, Madagascar, Mali, and Senegal were marked as countries with a relatively large gap between actual and potential yields. The major difference between the outcomes of HarvestChoice (2013) and our results is that their actual yields, which encompassing the influence of both social and physical measures, were compared with potential yields, which was defined as the yield without any climate

and nutrition stress; while we measured the gap according to the degree of exposure to climate stresses.

In this study, we do not discuss on the socio-economic factors which might influence vulnerability, as it is beyond the scope of this study and will be investigated in the follow-up study. However, the influence of these factors is reflected in the $CVDI_{soc}$. In Tanzania, for example, lower $CVDI_{soc}$ may be related to research and extension efforts applied in the fields as well as the use of improved maize seeds (Stephen et al., 2014). While in Nigeria strategies such as using hybrid varieties of seeds, availability of subsidized fertilizer, as well as improved infrastructure and extension services may have helped to adapt to climate variability. The maize revolution in Nigeria advanced the country to the tenth largest producer of maize in the world, and the largest maize producer in Africa. Democratic Republic of Congo suffered from years of war and political upheaval, and continues to face significant humanitarian challenges. No significant improvement in maize yield is reported over the last three decades. In Kenya, maize yield increased after liberation, however, it showed a slight decline between 1980 and 2013 presumably due to a lack of access to credit and finance to enable adoption of improved seeds (Abate et al., 2015).

Finally, the degree of vulnerability might vary over time, but we here quantified it for the whole studied period. Therefore, the social vulnerability of Nigeria with high maize yield in the last decade is of the same magnitude in Somalia where highest maize yield was seen in the first decade. In Nigeria, the most significant changes occurred after 2000. On the other hand, Somalia had its peak in maize production in the 1980's and the country experience an average of about 57% decrease over the last two decades in maize production in 1990's and 2000's due to famine, damages from pest, ethnic wars, and regime change. All these changes resulted in poor nutritional status of farmers, and fields being abandoned due to insecurity (Rashid and Zejjari, 1997). Similar situation occurred in Madagascar where yield increased after 2000 and therefore the country were placed as socially vulnerable regions.

4.3. Conclusion and limitation

Our proposed methodology quantified the physical and social crop drought vulnerabilities and highlights countries where adaptation capacities are weak. The results show that southern and eastern

African countries are physically more vulnerable to drought as compared to other regions. Central and western Africa, however, are socially highly vulnerable.

The standardized procedure used in calculating *DEI* and *CFI* provides a consistent comparison of crop drought vulnerability across regions and countries. It is also helpful for comparing *DEI* with *CFI* severities (Figs. 3&4), as a certain value of *DEI* or *CFI* indicates the same degree of severity. These two features together are effective for forward projection of vulnerability under future scenarios of climate change and help policy makers to estimate future risks of crop drought vulnerability. Besides, the physical and socioeconomic drought vulnerability maps obtained from the probability based linkage of *DEI* to *CFI* provide the needed geographical bases to identify vulnerable hotspots in both perspectives giving deeper insights to early warning of drought. The information enables regional and national policy makers to better characterize drought vulnerability across regions and prioritize proactive and reactive agricultural adaptation strategies in response to drought.

Moreover, there are generic strategies that can be implemented to combat drought vulnerability. These strategies are different in different regions, being physically less reliable in regions that are socioeconomically more vulnerable. The comparison of physical and socioeconomic vulnerabilities represents how countries cope with drought. Based on such comparisons, managers and policy makers will adopt different strategies based on the nature of vulnerability (physical or socioeconomic). The quantification approach proposed in this paper can be expanded in future studies to measure the degree of reduction in two crop drought vulnerability types in response to implementing different management scenarios.

Our analysis of social vulnerability was limited to the country scale due to the lack of spatially well-resolved crop yields which was the main limitation of this study. However, it is evident that the proposed methodology is valid and can be adapted to any spatial scale depending on the available data for the region. Smaller resolution of data will help to increase the reliability of the calibrated models and to better understand the effectiveness of adaptation strategies can be applied to each regions. Here, we assumed that social vulnerability is the same in all grids within the country and equals the average of the country.

This study does not provide a detailed investigation of factors that influence the difference between physical and social vulnerability. However, our preliminary discussion of the social drought vulnerabilities in SSA countries shows that such a systematic analysis would provide a more reliable basis for analysis of crop production risks and failure in various regions.

Acknowledgements

This study was supported by the Swiss National Science Foundation (SNF No.: CR21I3_146430. Dec.2013-Nov.2016).

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Highlights

- Maize was simulated using EPIC crop model at 0.5° level
- Vulnerability was defined based on the interaction of drought exposure and crop failure indices
- Physical and social maize drought vulnerabilities were mapped over SSA.
- Social vulnerability were higher in most regions.