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Research Application Summary

Vulnerability of people to climate change: influence of methods and computation approaches on assessment outcomes

Fandohan, A.B.,[1*] Sodé, A. I., [4] Bonou, A., [3] Ba, M. [2] & Salako, K. V. [4]

[1]Université Nationale d'Agriculture, Campus de Kétou, BP 43, Kétou, Benin
[2]WASCAL, University of The Gambia, MDI Road, Kanifing, P.O. Box 3530, Serrekunda
[3]Université Nationale d'Agriculture, Campus de Porto Novo, 01 BP 55, Porto Novo, Bénin
[4]Université d'Abomey Calavi, Campus de Calavi, 04 BP 1525, Cotonou, Bénin
Corresponding author: bfandohan@gmail.com

Abstract

Climate change has become a major concern globally, particularly to rural communities who have to find rapid coping solutions. Several vulnerability assessment approaches have been developed in the last decades. This comes along with higher risk of using different methods resulting in sometimes different conclusions thereby making comparisons difficult and decision making non-consistent across areas. We assessed effect of methods and computational approaches on estimates of people's vulnerability using data collected from the Gambia. Twenty four indicators reflecting vulnerability components (exposure, sensitivity, and adaptive capacity) were selected for this purpose. Data were collected through household surveys and key informant interviews. One hundred and fifteen respondents were surveyed across six communities and two administrative districts. Results were compared over three computational approaches: the maximum value transformation normalization, the z-score transformation normalization, and simple averaging. Regardless of approaches used, communities that have a high exposure to climate change and extreme events were the most vulnerable. Furthermore, vulnerability was strongly related to the socio-economic characteristics of farmers. The survey evidenced variability in vulnerability among communities and administrative districts. Comparing output across approaches, overall, people in the study area were found to be highly vulnerable using the simple average and maximum value transformation, whereas they were only moderately vulnerable using the z-score transformation approach. We suggest that assessment approach-induced discrepancies be accounted for in international debates to harmonize/standardize assessment approaches in order to makeg outputs comparable across regions. This would increase relevance of decision making for adaptation policies.

Key words: Gambia, maximum value transformation, simple averaging, vulnerability assessment, West Africa, z-score transformation

Résumé

Le changement climatique est devenu une préoccupation majeure à l'échelle mondiale, en particulier pour les communautés rurales qui doivent trouver des solutions d'adaptation rapides. Plusieurs approches d'évaluation de la vulnérabilité ont été développées au cours des dernières décennies. Cela s'accompagne d'un risque plus élevé d'utiliser différentes méthodes, ce qui aboutit à des conclusions parfois différentes et rend les comparaisons difficiles et la prise de décision

non cohérente d'un domaine à l'autre. Nous avons évalué l'effet des méthodes et des approches informatiques sur les estimations de la vulnérabilité des personnes à l'aide de données recueillies en Gambie. Vingt-quatre indicateurs reflétant les composantes de la vulnérabilité (exposition, sensibilité et capacité d'adaptation) ont été sélectionnés à cette fin. Les données ont été recueillies par le biais d'enquêtes auprès des ménages et d'entretiens avec des informateurs clés. Cent quinze répondants ont été interrogés dans six communautés et deux districts administratifs. Les résultats ont été comparés sur trois approches de calcul : la normalisation de la transformation de la valeur maximale, la normalisation de la transformation du score z et la moyenne simple. Quelles que soient les approches utilisées, les communautés fortement exposées aux changements climatiques et aux événements extrêmes étaient les plus vulnérables. De plus, la vulnérabilité était fortement liée aux caractéristiques socio-économiques des agriculteurs. L'enquête a mis en évidence la variabilité de la vulnérabilité entre les communautés et les districts administratifs. En comparant les résultats entre les approches, dans l'ensemble, les personnes de la zone d'étude se sont révélées très vulnérables en utilisant la simple transformation de la moyenne et de la valeur maximale, alors qu'elles n'étaient que modérément vulnérables en utilisant l'approche de transformation du score z. Nous suggérons que les écarts induits par les approches d'évaluation soient pris en compte dans les débats internationaux afin d'harmoniser/normaliser les approches d'évaluation en vue de rendre les résultats comparables entre les régions. Cela augmenterait la pertinence de la prise de décision pour les politiques d'adaptation.

Mots clés : Gambie, transformation de la valeur maximale, moyenne simple, évaluation de la vulnérabilité, Afrique de l'Ouest, transformation du z-score

Introduction

Climate change is defined as changes in the state of the climate due to either natural internal process in the climate system or external forces (IPCC, 2013). In the last two decade, it has become a major concern worldwide especially in rural areas where its negative effects are faced through crop failure and reduction in income (Ampomah *et al.,* 2012). Improving the capacity of people to deal with the negative effects of climate change is an essential step toward increasing their adaptive capacity. Howvever, developing and implementing adaptation policies requires an understanding of who is vulnerable. To what are they vulnerable? And why are they vulnerable? Answers to these questions would help policy makers understand the processes underlying farmers' vulnerability to climate change and put into place relevant copping strategies that will at least reduce their vulnerability and at best, climateproof local systems.

Vulnerability is the susceptibility of a system to be affected by climate change (IPCC, 2013). It is a function of exposure, sensitivity, and adaptive capacity. There are several approaches to measure climate vulnerability using a range of indicators operating both at different scales: simple average of indicators without normalization and average of indicators with normalization (maximum value and z-score transformations). The relation between the three independent endogenous elements of climate vulnerability index (CVI) may not be governed by local circumstances. However, vulnerability is a positive function of the system's exposure and sensitivity and a negative function of the system's adaptive capacity (Ford and Smith, 2004). Several methods have been developed to assign weights to vulnerability components. For example, the balanced weighted average approach (Sullivan and Meigh, 2005) was used for CVI due to the various and ambiguous shares and relationships of different components with each other. There are different computation and transformation approaches to measure vulnerability of a system; yet, their effect on conclusions about the level of vulnerability among people is largely overlooked. This study is an attempt to fill in this gap. Using data from the North Bank Region of the Gambia as a case study, it aimed at assessing effect of methods and computation approaches on the vulnerability index of local farmers facing adverse effects of climate change. The objectives of the study were to (i) estimate the vulnerability index of local farmers to the adverse effects of climate change in two districts and (ii) assess the effect of computation and normalization approaches on the conclusions about their level of vulnerability.

Methodology

Study system. The North Bank region of the Gambia is highly exposed to drought chocks as a result of changes in rainfall patterns. It thus represents a good case for our study. Two districts in the North Bank Region of the Gambia were considered for this study: Lower Baddibu and Jokadu. The Gambia is located in the West Coast of Africa between latitude 13 and 14 degrees North and 13 and 17 degrees West. With a population size of 1 882 450 persons (GBOS, 2013), the Gambia has an estimated area of 11,300 km^2 of which 10,000 km^2 is covered by land, and 1300 km^2 is covered by water. The Gambia is land-locked inside Senegal in the South, the North and the East, and is bordered by the Atlantic Ocean in the West. The river Gambia flows through the country from the East into the Atlantic Ocean in the West, and dissects the country into a northern and southern part.

Household survey. This research assessed the vulnerability of farmers in the North Bank Region of the Gambia to selected climate change factors and extreme event based on an indicator approach. Twenty four indicators which reflect the component of vulnerability: exposure, sensitivity, and adaptive capacity, were selected for the purpose of this work (Table 1). Data were collected through a household survey and key informant interview on 115 farmers (57 in Jokadu and 58 in Lower Baddibu). This sample size was retained after applying Dagnelie's (1998) formula to the percentage of people that are aware and affected by environmental changes over 102 people selected randomly for the explanatory survey. The information obtained from the household survey was used to determine the vulnerability index computed using three different formulas defining the relation between exposure, sensitivity and adaptive capacity.

Data processing. In the climate change literature, vulnerability is understood as a function of biophysical and socio-economic factors (O'Brien *et al.,* 2004). The proposed climate vulnerability index comprises three main dimensions or components that are: sensitivity, exposure and adaptive capacity. The Adaptive capacity includes socio-demographic profile, livelihood strategies and social networks; sensitivity deals with health, food, water components and exposure accounts for natural disasters and climate variability that a given system is faced with.

In this study, two approaches of normalization namely: maximum value and z-score transformations and another one without normalization (simple sum of scores) and three computation methods were used to estimate the indexes of vulnerability.

The computation methods used in this study are given as follows:

(1) Additive relationship with sensitivity and exposure

CVI = (Exposure + Sensitivity) – (Adaptive Capacity)

(2) Multiplicative relationship with sensitivity and exposure

Table 1. Indicators selected for the purpose of this work

Component of vulnerability	Aspect of vulnerability or sub-component	Indicators
Sensitivity	Environment and Socioeconomic	Household size, income source; land ownership; source of food, reliance on traditional farming tools; soil erosion; type of agriculture practice; labor support, number of months covered by crop production, farm structure
Exposure	Environment	Frequency of extreme events(heavy rainfall, flood, wind storm), changes in climatic condition (Temperature, Rainfall); salt intrusion, crop pest
Adaptive capacity	Environment and Socioeconomic	Level of education, use of irrigation system, diversity of livelihood sources, social network system, Institutional support; climate change awareness, cash income utilization

CVI = *(Exposure * Sensitivity) – (Adaptive Capacity)*

(3) Inverse relationship with sensitivity

CVI = 1 - | *(N1*Exposure –N2* AC)/(N1+N2)* |**(1/Sensitivity)*

Where Ni represents the number of sub-components used to compute a given component of vulnerability (eg. In this study, Ni equals 2 for Sensitivity and Adaptation, and 1 for Exposure). For this method, a high CVI reflects low vulnerability).

With regard to the normalization approaches, we used:

(4) The Raw score without normalization

In this approach, a simple sum of indicators' scores was used to determine the values of each component of vulnerability, i.e., exposure, sensitivity, and adaptive capacity:

NS Σ score$_{\text{indicator}}$; where NS is the non-transformed score for a given CVI component.

(5) The Maximum value transformation

According to Yoon (2012), this technique is used to rescale values between 0 and 1:

$MS = \sum \frac{\text{score}_{\text{indicator}}}{\text{maximum score}}$; where MS is the maximum value transformation score for a given CVI component.

(6) The Z-score transformation

This method helps to covert the indicator to a common scale with a mean of zero and a standard deviation of one (Yoon, 2012).

$ZS = \sum \frac{\text{score}_{\text{indicator}} - \text{mean}}{\text{standard deviation}}$; where ZS is the z-score transformation for a given CVI component whereas the mean and standard deviation are computed for an indicator across respondents.

Assuming r to be the range of CVI values, three vulnerability levels were defined: CVI values falling between lowest value and 1/3r (for the additive and the multiplicative relationship) or the maximum value and 2/3r (for the inverse relationship), is considered as less vulnerable; CVI between the 1/3r and 2/3r is considered as moderately vulnerable; CVI between the maximum and the 2/3r (for additive and multiplicative relationship) or the minimum and 1/3r (for inverse relationship), is considered as highly vulnerable.

Computations and graphics were performed in MS Excel and R software version 3.2.2. Statistical significance of differences between the two districts were assessed using either the t test or Wilcoxon test, depending on whether the data fulfill normality and equality of variance criteria or not.

Results

The vulnerability of farmers to climate change (changes in rainfall and temperature) and extreme event was determined through a Climate Vulnerability Index (CVI) computed from primary data (socio-economic and biophysical) collected through a household survey.

Components' scores according to the transformation approaches. In raw scores-based results, exposure had a higher contribution to the CVI index than sensitivity, whereas outputs for the maximum score transformation, illustrated a higher contribution of sensitivity to the level of vulnerability of surveyed people. In order words, using the same data set, the raw score indicated that people were more sensitive than exposed while the maximum transformation suggest the opposite figure. With Z-score transformation, exposure was higher for one district while sensitivity was higher in the second one (Table 2).

Comparison of average CVI for different districts according to the computation and transformation approaches. The results of the study show that communities that have a high exposure to climate change and extremes were more vulnerable. Overall, with the first two computation methods (additive and multiplication function of sensitivity and exposure), the study districts were found to be moderately vulnerable using the simple average and maximum value transformation, whereas the two were less vulnerable when the z-score transformation approach was used (Figures 1, 2 and 3; Table 3). Using the inverse function of sensitivity method, one of the two districts (Lower Baddibu) which was moderately vulnerable to climate change with the two other computation methods became less vulnerable (Figures 1, 2 and 3; Table 3) when the row scores or the maximum value transformation were used. No computation approach showed high vulnerability of studied districts to climate change according to the levels defined in this study.

Table 2. Average components scores by transformation approach per district

Transformation	Districts	Exposure	Sensitivity	Adaptive capacity
Raw	Jokadu	16.68	12.88	10.49
	Lower Baddibu	16.57	13.07	11.12
Maximum	Jokadu	5.55	6.33	3.02
	Lower Baddibu	5.52	6.4	3.85
Z-score	Jokadu	-0.01	-0.2	-0.78
	Lower Baddibu	0.02	0.04	0.78

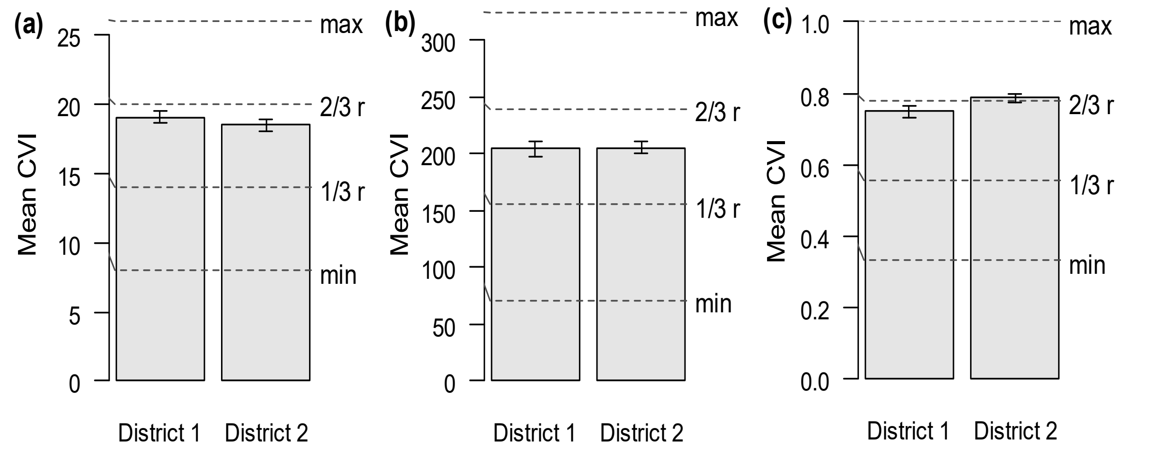

Figure 1. Average CVI of districts using raw score of indicators -- (a) CVI as additive relationship with sensitivity and exposure; (b) CVI as multiplicative relationship with sensitivity and exposure and (c) CVI as inverse relationship with sensitivity; District = Jokadu and District 2 = Lower Baddibu; 1/3 r = third of the range of CVI (i.e. max–min) and 2/3 r two third of the range.

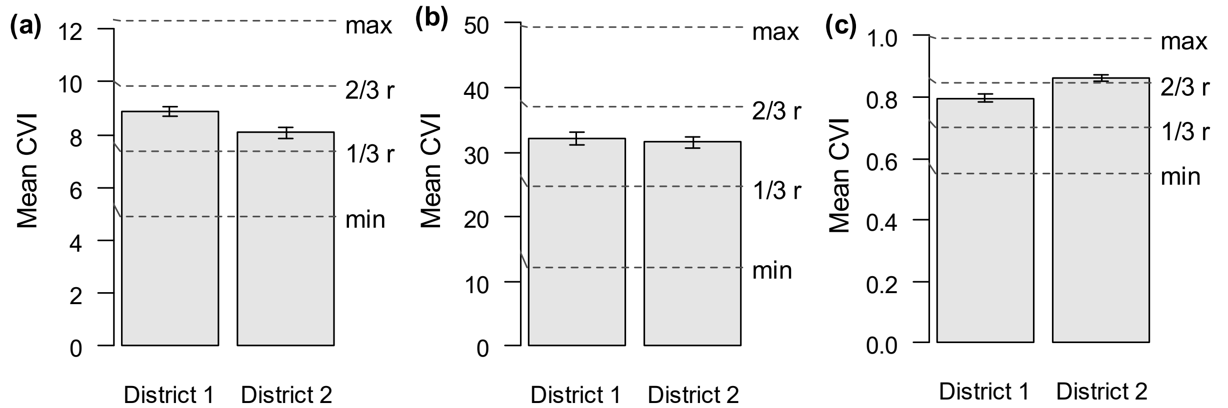

Figure 2. Average CVI of districts using maximum score transformed indicators -- (a) CVI as additive relationship with sensitivity and exposure; (b) CVI as multiplicative relationship with sensitivity and exposure and (c) CVI as inverse relationship with sensitivity; District = Jokadu and District 2 = Lower Baddibu; 1/3 r = third of the range of CVI (i.e. max–min) and 2/3 r two third of the range

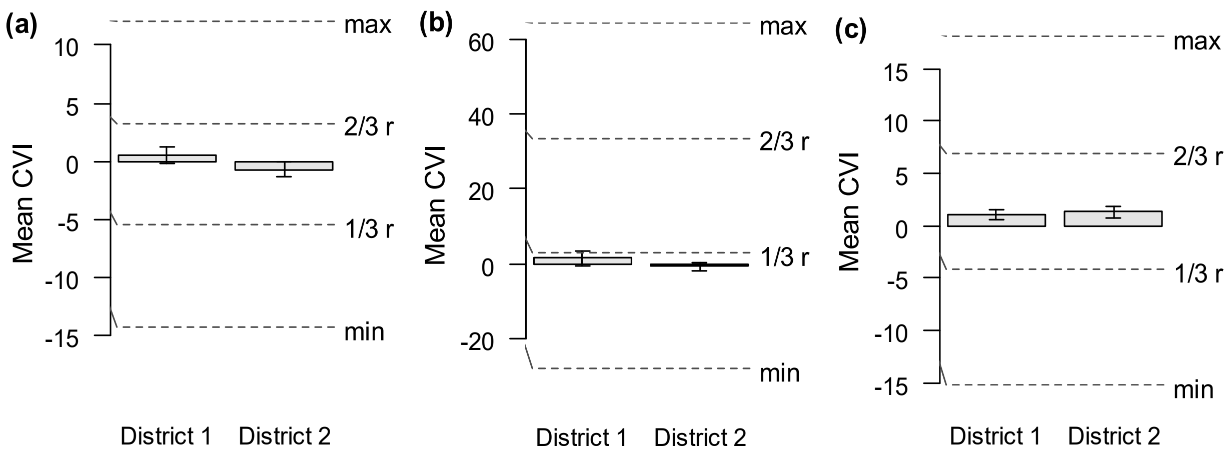

Figure 3. Average CVI of districts using Z-score transformed indicators -- (a) CVI as additive relationship with sensitivity and exposure; (b) CVI as multiplicative relationship with sensitivity and exposure and (c) CVI as inverse relationship with sensitivity; District = Jokadu and District 2 = Lower Baddibu; 1/3 r = third of the range of CVI (i.e. max–min) and 2/3 r two third of the range.

Table 3. Vulnerability level of districts according to different methods of computation

	Simple score		Maximum score		z-score	
Computation approach	Jokadu	Lower Baddibu	Jokadu	Lower Baddibu	Jokadu	Lower Baddibu
Sum	Moderate	Moderate	Moderate	Moderate	Moderate	Moderate
Product	Moderate	Moderate	Moderate	Moderate	Low	Low
Inverse	Moderate	Low	Moderate	Low	Moderate	Moderate

In the case of the third computation method (c), CVI is function of inverse of sensitivity; thus, a system is highly vulnerable in that if its CVI index has a low value

Comparison of vulnerability levels among districts according to the computation methods. Using additive and inverse function of sensitivity for CVI computation, only maximum score transformation gave significant difference between the two districts (t or Wilcoxon test, Prob. < 0.05; Table 4). Although the two districts were viewed as moderately vulnerable using raw scores, the level of vulnerability of Jokadu district was statistically significantly higher than that of Lower Baddibu district in those cases.

Table 4. Results of Wilcoxon or t-test comparing districts vulnerability levels per method

Transformation	Computation methods	Tests	Statistiques	df	P-value
Raw score	Sum	Wilcoxon	1797		0.419
	Product	t	-0.105	108.91	0.916
	Inverse	Wilcoxon	1418	0.189	
Maximum score	Sum	t	2.822	112.9	0.005
	Product	t	0.459	111.5	0.646
	Inverse	Wilcoxon	1008.5		<0.001
Z-score	Sum	t	1.319	111.73	0.189
	Product	Wilcoxon	1847		0.279
	Inverse	Wilcoxon	1625		0.877

Discussion

A comparative analysis was performed to unfold discrepancies in the outcomes of different vulnerability-to-climate-change assessment methods and computation approaches. This study confirmed expected divergences in the results. It was found that with the two first computation approaches (additive and multiplicative method) and the two first transformation approaches (simple sum without normalization, and maximum value transformation), farmers in the two compared samples were moderately vulnerable to climate change, while with the z-score transformation, they were less vulnerable. This may be due to the normalization method used which gave different values to the indicators, especially with the z-score transformation, where most of the values were negative. Nevertheless, the normalization approach gives a more comprehensive result as it shows

variation in the level of communities' exposure, sensitivity, and adaptive capacity. On the other hand, it has been illustrated that z-score transformation may result in reduction of statistical test's power as compared to tests with simple raw values (Strobl and Zeileis, 2008). This may also be the underlying driver of the observed divergences in the results of the present study.

The concept of vulnerability is multidimensional and place specific. Therefore, it can be a function of target communities' intrinsic characteristics. Because results may be sensitive to the method and computation approach used (Hahn *et al*., 2009; Etwire *et al*., 2013), interpretations and comparing over different communities must be done with caution.

Conclusion

The index of vulnerability is a useful tool which allows measuring a system' vulnerability. However, in general it is associated with some problems that should not be ignored in interpretations. This piece of work highlights the differences in the outcomes of different methods and approach to assess the index of vulnerability. It showed that whatever the transformation method, the vulnerability index computation based on an additive relationship between sensitivity and exposure results in the same vulnerability level, contrary to the multiplicative and inverse value approach which sometimes yield different levels of vulnerability across transformation methods. Yet, a multiplicative relationship between sensitivity and exposure would make more sense sensu statistica. Accounting for those divergences and proposing a standardized approach across study areas will make results more relevant to policy.

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