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PSYCHOMETRIC ANALYSES OF MULTIDIMENSIONAL CLIMATE-RELATED VULNERABILITY MEASURES IN GHANA, KENYA, AND SOUTH AFRICA

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DISCLAIMER

All opinions, interpretations and conclusions expressed in this Transforming Social Inequalities through Inclusive Climate Action (TSITICA) Working Paper are entirely those of the authors and do not reflect the views of the research funder UK Research and Innovation (UKRI).

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The Transforming Social Inequalities Through Inclusive Climate Action (TSITICA) project investigates how climate change action can be socially transformative in three contrasting African countries: Ghana, Kenya and South Africa. The research agenda addresses the nexus between climate change, sustainable livelihoods and multidimensional poverty and inequality to tackle the overall question: how can climate actions be deliberately targeted to improve livelihoods and lead to equitable benefits for the most vulnerable and poor – especially for women and youth? With the goal of inspiring climate actions that also reduce poverty and inequality, based on evidence and insights from the research, TSITICA aims to contribute the Agenda 2030 ambition of leaving no one behind.

The full project team comprises researchers from two African Research Universities Alliance (ARUA) Centres of Excellence hosted by the University of Cape Town (UCT); researchers from the centres' regional nodes at universities in Ghana and Kenya; and collaborators from four universities in the United Kingdom:

• African Centre of Excellence for Inequalities Research, hosted by UCT's Southern Africa Labour and Development Research Unit, School of Economics

• ARUA Centre of Excellence in Climate and Development, hosted by UCT's African Climate and Development Institute

• ARUA-CD and ACEIR nodes convened respectively by the Institute for Environment and Sanitation Studies and the Institute of Statistical, Social and Economic Research, University of Ghana

• ARUA-CD and ACEIR nodes convened respectively by the Institute for Climate Change and Adaptation and the School of Economics, University of Nairobi

• Grantham Research Institute on the Environment and Climate Change, London School of Economics and Political Science

• Townsend Centre for International Poverty Research, University of Bristol

• International Inequalities Institute, London School of Economics and Political Science

• Tyndall Centre for Climate Change Research, University of East Anglia

• Tyndall Manchester, University of Manchester

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Abstract

People in vulnerable situations are disproportionately affected by climate change. Nonetheless, the majority of available climate-related multidimensional vulnerability indicators and assessments are at the national or regional level, with individual and household level disparities not being fully considered. The objectives of this paper are twofold: first, we analyse climate-related multidimensional vulnerability measurements, focusing on individual and household characteristics in Ghana, Kenya, and South Africa; second, we examine the psychometrics analyses of the indicators to evaluate their reliability and validity in terms of measuring multidimensional climate-related vulnerability across the three countries. The multidimensional vulnerability analysis demonstrates that poor and rural households are more likely to be vulnerable to climate-related impacts in all three countries. Although the primary indicators driving overall multidimensional vulnerability varies among the three countries, employment type, access to basic services, food insecurity, and demographic factors are all important factors in the three countries. Our psychometrics analyses of the indicators demonstrated that lack of access to safe water and sanitation, and food insecurity were reliable and valid climate vulnerability indicators across the three countries.

Keywords: climate change, vulnerability, inequality, psychometric analysis, Africa

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Introduction

Climate change intensifies the hydrological cycle, bringing more frequent and intense storms, floods, landslides, and droughts. It also causes the oceans to warm, expand and acidify. Changes may occur to "typical" weather patterns and current ocean circulation. Climate change also affects different areas in different ways. For example, Kenya is arguably a land of lakes. During the past decade, many Kenyan Great Lakes have significantly increased in volume, flooding homes, schools, and other infrastructure. By contrast, parts of South Africa have suffered from water shortages over the past few years.

It is a truism that poor people are more vulnerable to environmental hazards, as they have few or no assets to fall back upon. However, equating climate change vulnerability with income poverty and/or multiple deprivations is crude, because not all poor people are equally vulnerable to the effects of climate change and not all non-poor people are immune to the climate effects. It would be preferable to measure vulnerability to climate change impacts using indicators directly related to a greater risk of harm based on robust normative criteria and scientific evidence.

In this paper, we define *climate-related vulnerability* at the level of individuals and households, and then use this framework to analyse climate-related multidimensional vulnerability in Ghana, Kenya, and South Africa. Then, we examine the psychometrics analyses of the indicators to evaluate their reliability and validity in terms of measuring multidimensional climate-related vulnerability across the three countries.

While there is a growing literature on climate change-related vulnerability indices within these domains, these measures are invariably at the national or, at best, regional level. To address this knowledge gap, we outline a set of potential indicators of climate change-related vulnerability at the individual and household levels by selecting 14 indicators that are classified into four dimensions: demographic, economic, household factors and nutrition (see Table 1). These indicators and any composite index at individual and/or household levels arguably measure individual-and household-level climate-related vulnerability.

Defining and measuring climate-related vulnerability

There has been intense discussion of the meaning of climate-related vulnerability in the environmental science and climatology literature, and several definitions have been proposed. For example:

"The intrinsic and dynamic feature of an element at risk that determines the expected damage/harm resulting from a given hazardous event and is often even affected by the harmful event itself. Vulnerability changes continuously over time and is driven by physical, social, economic and environmental factors" (Birkmann, Joern & Wisner, 2006).

"*Vulnerability is related to the characteristics and circumstances of a community or system; these characteristics and circumstances make a community or system susceptible to hazard and cause loss. Many aspects of vulnerability arise from various physical, social, economic, and environmental factors. Examples may include poor design and construction of buildings, inadequate protection of assets, lack of public information and awareness, limited official recognition of risks and preparedness measures, and disregard for wise environmental management*" (UN-ISDR, 2019).

An overview of this literature suggests that most climate-related vulnerability indices attempt to measure two major components of vulnerability- sensitivity as well as coping and adaptive capacity (see IPCC, 2022). In particular, *sensitivity* indicates the extent to which a system is affected due to the impact of climate change impacts; while coping and adaptive capacity indicates the system's ability to manage and overcome adverse conditions, and ability to recover from the prior state or achieve desired post-disaster state. These vulnerability components often are measured mostly at the national or regional level (e.g., Global Climate Risk Index[1], INFORM[2]).

Fewer studies use individual or household-level indicators to measures multidimensional climate-related vulnerability. Some indicators used in Latin American studies are improved water and sanitation, undernourishment, underweight children, child mortality and GDP per capita (Ludena & Yoon, 2015). In India, indicators used include the household dependency of ratio, literacy of the head of household, household with members who have migrated, fodder and firewood collection, crop varieties, agricultural work as a primary job, household debt, receipt of government or social support, infant and adult mortality, food insecurity, fertiliser and pesticide use, water availability and source (Pandey & Jha, 2012). In China, some indicators used include water, income and food sources, amount of land owned, education level, household dependency ratio, housing conditions, consumer durables, per capita income, number of relatives and amount of social support (Zhang et al., 2018).

In this paper, we propose to use 14 indicators, grouped into four dimensions: economic, demographic, housing, and nutrition status. These indicators primarily focus on the elements of vulnerability that influence people' sensitivity and their coping abilities (see Shifa et al., 2023). All the three country case studies adopted the dimensions and indicators proposed in Table 1. However, due to data limitations and local context considerations, not all the dimensions and indicators are measured in exactly the same manner across the three countries.

In South Africa and Ghana, the number of dimensions and indicators are the same (see Shifa et al., 2023; Osei et al., 2023). In the case of Kenya, the datasets used have no

[1] See https://www.germanwatch.org/en/cri
[2] See https://drmkc.jrc.ec.europa.eu/inform-index/

information about pregnancy (Manda et al.,2023), therefore, the demographic dimension does not include "pregnant women" as an indicator. Food insecurity is measured differently in these three countries. In South Africa, a household is considered food insecure, if its per capita income is less than the food poverty line. In Ghana, a household is considered food insecure, if the total food expenditure is less than two-thirds of the national average. In Kenya, a household is food insecure, if the respondent answered "yes" to the perception of food insecurity questions. In Kenya, the employment vulnerability indicator is measured using three different indicators: subsistence farming, pastoralist work and informal work.

Table 1 List of Vulnerability Dimensions and Corresponding Indicators

Dimensions	Indicators
Demographic	1) **Younger children** (under 10) are known to be vulnerable to harm during flooding as they are relatively short and light and cannot swim very well or flee quickly (Mort et al., 2018; Muttarak & Dimitrova, 2018). Babies (under 12 months) are also at risk of heat stress as they have more limited temperature regulation than older children and adults.
	2) **Pregnant women** are at a higher risk of spontaneous abortion, low birth weight, neonatal deaths, congenital anomalies, and maternal mortality due to flooding (Mallett & Etzel, 2017).
	3) **Older people** (aged 60 and 60+) are known to be vulnerable to heatwaves with circa 80-90% of excess mortality from heat stress occurring in this age group (Kenny et al., 2010), particularly amongst those suffering from obesity, cardiovascular disease, respiratory disease, and diabetes.
	4) **Disabled people** are often at greater risk of harm during extreme climate events (Gutnik & Roth, 2018). Disability is measured in many ways, but ideally, the results from an international harmonised measure should be used, such as the Washington Group Short Question Set[3] or the WHO Model Disability Survey[4] questions.
Economic	5) **Subsistence farmers, fishers, hunters and gatherers** (ISCO-08 = 63)
	6) **Building and related trades workers** (excluding electricians) (ISCO-08 = 71)
	7) **Agricultural, forestry and fishery labourers** (ISCO-08 = 91)
	8) **Street and related sales and service workers** (ISCO-08 = 95)

[3] See http://www.washingtongroup-disability.com/
[4] See https://www.who.int/disabilities/data/brief-model-disability-survey5.pdf?ua=1

Household	9) **Inadequate housing construction**: mud/earth floor, and natural materials for walls/roofs are vulnerable to storms. 10) **Inadequate water supply:** surface water as defined by the JMP drinking water ladder[5] makes households vulnerable to both drought and floods. 11) **Inadequate sanitation:** open defecation and unimproved sanitation as defined by the JMP sanitation ladder[6] make households vulnerable to sewerage contamination during floods. 12) **Inadequate information access:** not having a radio, TV, mobile or landline telephone or internet access reduces the likelihood of receiving disaster warnings and other relevant and potentially life-saving information.
Nutrition	13) **Food Insecurity:** FAO Food Insecurity Experience Scale[7] (SDG threshold moderate to severe food insecurity). 14) **Anthropometric failure**: Comprehensive Index of Anthropometric Failure (CIAF), i.e., children (under 5) who are stunted, wasted or underweight (< 2SD below the WHO international reference population; see Nandy & Svedberg, 2011).

In all the country case studies, more than one data source was used in order to analyse multidimensional climate-related vulnerability over time and across spatial and social groups. In the case of South Africa, the National Income Dynamics Survey (NIDS) and the 2016 Community survey were used; for Ghana, the Socioeconomic Panel Survey (GSEPS) datasets were used; and for Kenya, the Kenya Integrated Household Budget Surveys (KIHBS) and the Kenya Population and Household Census data were used (see Shifa et al., 2023; Osei et al., 2023; Manda et al.,2023 for details).

Results

An Overview of Inequalities in Multidimensional Vulnerability

We present an overview of the disparities in multidimensional vulnerability in the three countries based on the most recent datasets used in each county study. More detailed analysis can be found in each case country paper (Shifa et al., 2023; Osei et al., 2023; Manda et al.,2023). We define vulnerable at the household level for all indicators. Figure 2 depicts the distribution of vulnerability indicators across the three countries. In all three countries, a relatively large proportion of households are vulnerable due to food insecurity, type of economic activities and demographic factors such as the presence of younger and older people. However, the degree of vulnerability in these indicators varies significantly across the three countries.

[5] See https://washdata.org/monitoring/drinking-water
[6] See https://washdata.org/monitoring/sanitation
[7] See https://www.fao.org/in-action/voices-of-the-hungry/en/

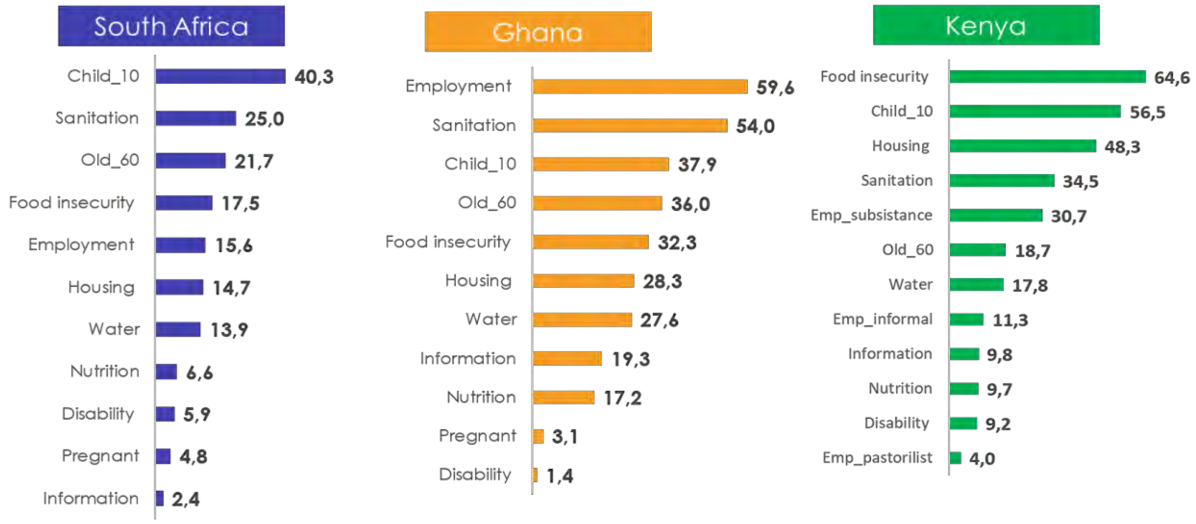

Figure 2: The Distribution of Vulnerability Indicators across the Three Countries
Notes: Authors' calculation based on NIDS (2017), KIHBS (2019) and GSEPS (2015-16) data.

Sanitation deprivation, for example, is the second most important factor in both Ghana and South Africa; however, the percentage of households vulnerable due to a lack of adequate sanitation in Ghana is twice that of South Africa. Similarly, the percentage of households without safe drinking water was around 14% in South Africa, 28% in Ghana, and 17% in Kenya. These findings indicate that, when compared to South Africa, access to basic services such as water and sanitation is a major issue in Ghana and Kenya.

Food insecurity is another common important factor across the three countries considered here. Although food insecurity is one of the top five important vulnerability indicators in all the three countries, it is the most pressing vulnerability indicator in Kenya, with close to 65% of households classified as food insecure, compared to 32% in Ghana and 18% in South Africa. The gap renames if we take into account the fact that the food insecurity indicator is measured slightly differently across the three countries. For instance, in the case of South Africa, the percentage of the population that can be considered food insecure, based on household self-reported perception of food insecurity, is about 24% (Shifa et al.,2023), which is much lower than the estimate for Kenya (65%).

Another common important factor is vulnerability due to the type of economic activities. Near 60% of households in Ghana were vulnerable due to the type of economic activities, compared to 40% in Kenya and 16% in South Africa. However, the composition of employment and thus the drivers of vulnerability in economic activities vary significantly across the three countries. This is primarily due to relatively higher participation in subsistence agriculture in Ghana and Kenya, whereas it is primarily due to employment in the non-agriculture sector in South Africa, where participation in subsistence agriculture is less than 4%.

Figure 3 and Figure 4 provide estimates of the multidimensional vulnerability index by location and poverty/wealth status. Multidimensional vulnerability is consistently higher in rural areas than in urban areas across the three countries. This is to be expected given that rural households are more vulnerable than urban households based on the majority of indicators in the three countries. In Ghana, for example, nearly 85% of rural households were vulnerable due to the type of economic activity, whereas only 42% of urban households were (see Osei et al., 2023). In South Africa, the proportion of the population that was vulnerable due to a lack of access to safe water is 34% in rural areas and 4% in urban areas (Shifa et al., 2023). Similarly, while 27% of rural households in Kenya lack safe water, only 6% of urban households were in such a condition (Manda et al., 2023).

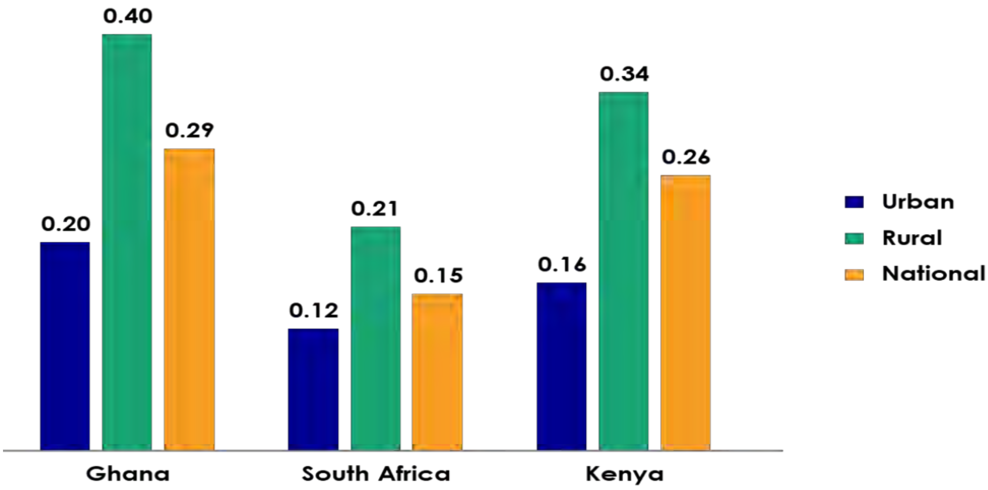

Figure 3: Multidimensional Vulnerability by Countries
Notes: Authors' calculation based on NIDS (2017), KIHBS (2019) and GSEPS (2015-16) data.

Poverty is another factor that exacerbates climate-related vulnerability. Figure 4 shows that those in the poorest income or wealth quintiles have a higher level of multidimensional vulnerability in all three countries. Moreover, the average vulnerability index is at least three times higher among those in the lowest income or wealth quintile than among those in the highest income quintile.

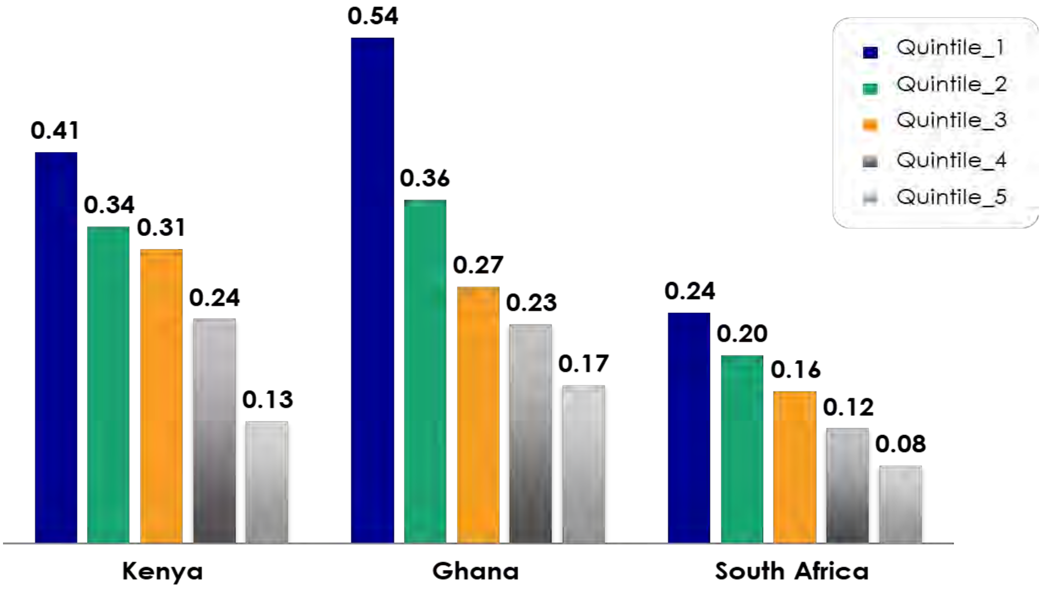

Figure 4: Multidimensional Vulnerability by Income/Wealth Quintile across Countries
Notes: Authors' calculation based on NIDS (2017), KIHBS (2019) and GSEPS (2015-16) data.

Overall, the multidimensional vulnerability analysis shows a consistent pattern across the three countries, namely that the poor and those living in rural areas are more vulnerable to the effects of climate-related shocks. There are also large disparities in the extent of multidimensional vulnerability across three countries within urban and rural areas (see Shifa et al., 2023; Osei et al., 2023; Manda et al., 2023). Although the ranking of the main indicators that drive the overall multidimensional vulnerability varies across the three countries, employment type, access to basic services, food insecurity, and demographic factors are all important in the three countries (see Figure 2 above).

The Psychometrics Analyses of the Vulnerability Indicators

The overall objective of the psychometrics analyses of the indicators is to evaluate their reliability and validity in terms of measuring multidimensional vulnerability to climate change. In particular, we aimed at 1) understanding the indicators' consistency (i.e., reliability), appropriateness (i.e., face validity) and relation with other variables associated with climate vulnerability (i.e., criterion validity); 2) identifying indicators that demonstrate a high level of reliability and validity across countries. The psychometric analyses were conducted according to the most updated *Standards for Educational and Psychological Testing Guideline* (2014).

The reliability tests contain the Classic Test Theory (CTT) and the Item Response Theory (IRT), with a focus on the internal consistency and precision of the vulnerability indicators. Following are the validity tests, which examine the indicators' criterion validity as presented above. Logistic regressions are implemented in the validity analysis.

Test of reliability

Classic Test Theory (CTT)

According to the CTT, Coefficients α, β, λ and ω were calculated for each country. A detailed explanation of the different reliability coefficients can be found in previous work, such as Zhang and Selwyn (2019). Table 2 summarises the reliability coefficients of the vulnerability indicators across the three countries.

Table 2 Reliability coefficients of the vulnerability indicators across countries

	Ghana	Kenya	South Africa
Maximum Split Half Reliability (i.e., Guttman λ4)	0.68	0.69	0.51
Guttman λ6	0.58	0.59	0.40
Average Split Half Reliability	0.54	0.57	0.38
Guttman λ3 (i.e., α)	0.56	0.57	0.38
Guttman λ2	0.59	0.59	0.41
Minimum Split Half Reliability (i.e., β)	0.31	0.40	0.21
Coefficient ω Hierarchical	0.56	0.60	0.21
Coefficient ω Total	0.63	0.66	0.48

Notes: Some items in the South African data were negatively correlated with the total scale. They were reversed before the reliability coefficients were produced. The paper discusses its implications.

The results demonstrate that all the reliability coefficients did not pass the conventional threshold of >=.70 for a high internal consistency (except for the Guttman λ4 coefficient of the Kenya data, which was .70). In the case of Ghana and Kenya, λ1 to λ6 were around 0.6 to 0.7. They are at the marginal of the convention threshold of .70 for a high internal consistency, suggesting that the indicators were just moderately reliable indicators of climate vulnerability. The relatively low-reliability coefficients indicate that the indicators measure different aspects (or dimensions) of climate vulnerability, which is hardly considered as a unidimensional phenomenon.

Item Response Theory (IRT)

Following this, the IRT is implemented to understand the capacity of each indicator to reflect the different levels of climate vulnerability. The IRT is a latent trait analysis model (Fontanella, et al., 2016; Zhang & Selwyn, 2019) that considers each indicator as a function of an underlying latent factor (i.e., climate vulnerability). In this study, we adopted a two-parameter logistic (2PL) IRT model, which generates two parameters of item (i.e., vulnerability indicator) characteristics. The first is an a-parameter of *item discrimination*, which illustrates whether each indicator is able to reflect changes at different levels of climate vulnerability; the second is a b-parameter of *item difficulty*, which suggests whether respondents are likely to endorse a positive response to an indicator (i.e., being vulnerable) given their current vulnerability level).

The item characteristic curves (ICCs) can be used to visualise the item a- and b-parameters. Specifically, at the same level of b-parameter (i.e., item difficulty), the slopes of ICCs are steeper for indicators with higher a-parameters (i.e., item discrimination). In other words, an S-shape ICC indicates that an indicator is more capable of distinguishing changes at different levels of climate vulnerability than indicators with a relatively flat ICC (see more detailed explanations in Fox, 2010; Zhang & Selwyn, 2019).

Figures 5 to 7 below illustrate the ICCs of vulnerability indicators for Ghana, Kenya and South Africa. For Ghana (Figure 5), the vulnerability indicators having high a-parameters include the type of employment, deprivation of sanitation facilities, shelter, water, food and information, and malnutrition.

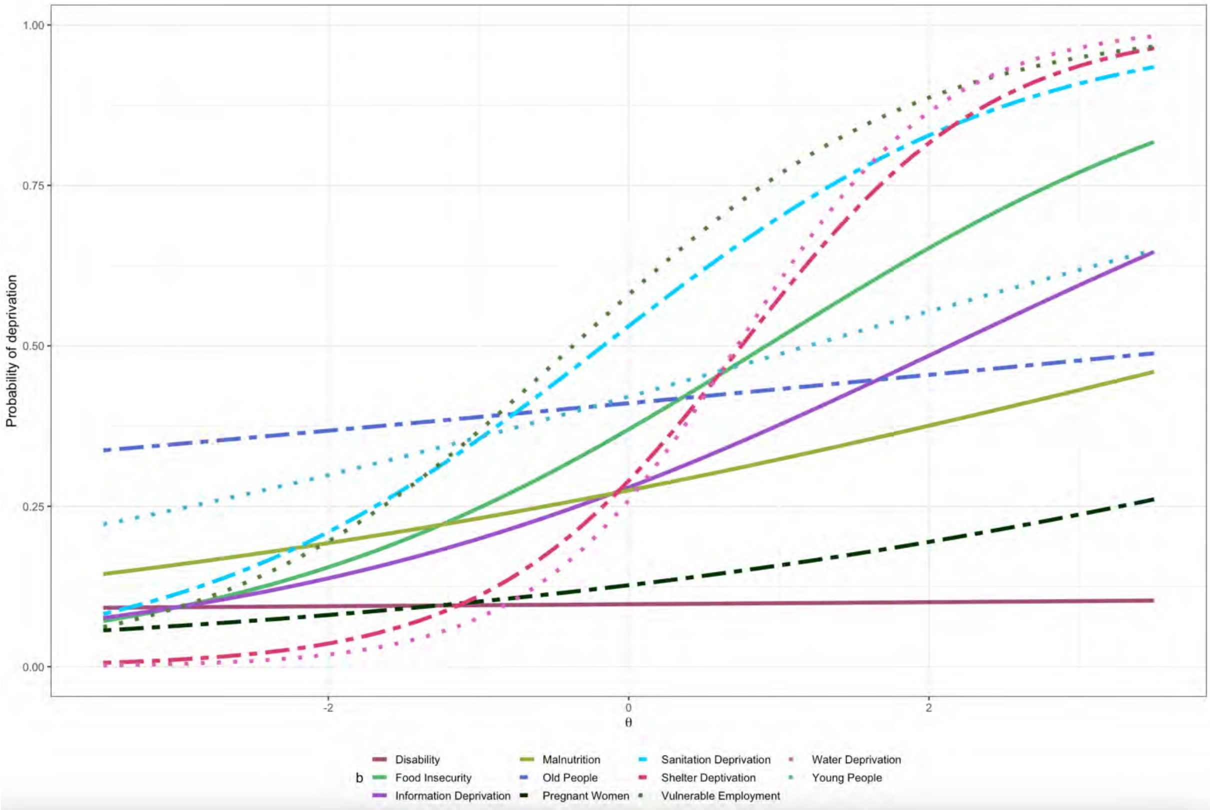

Figure 5 ICCs of Climate Vulnerability Indicators in Ghana

Likewise, for Kenya, the vulnerability indicators having high a-parameters include deprivation of food, shelter, sanitation facilities, water and information as well as being in pastoralist households.

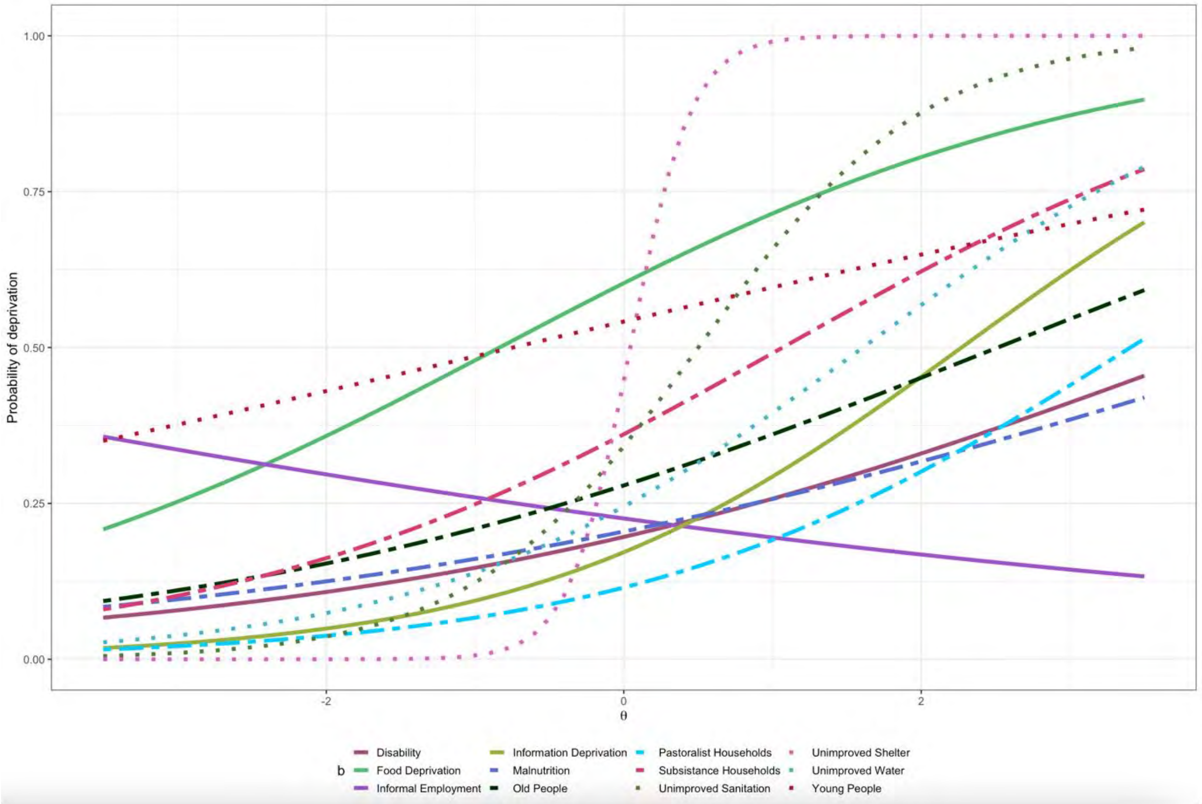

Figure 6: ICCs of Climate Vulnerability Indicators in Kenya

Last but not least, for South Africa, the vulnerability indicators having high a-parameters include malnutrition, deprivation of food, sanitation facilities and water, as well as being young people under the age of 10.

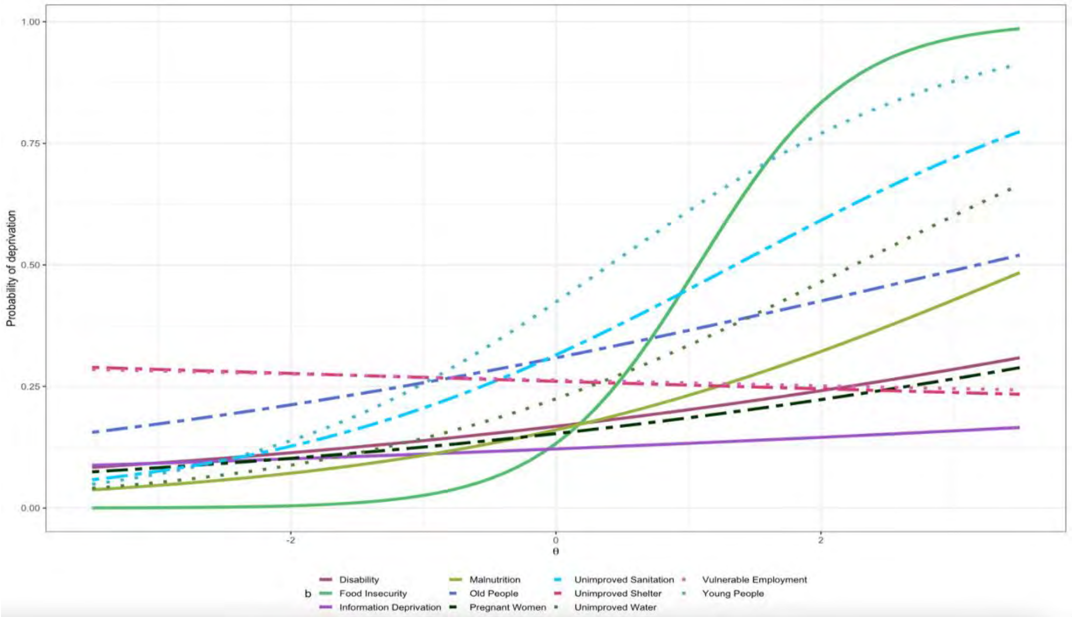

Figure 7: ICCs of Climate Vulnerability Indicators in South Africa

Consistent with the ICCs, the item (i.e., indicator) discrimination and difficulty scores are displayed in Table 3.

Table 3 Item/Indicator Discrimination (a) & Difficulty (b) of Vulnerability Indicator across Countries

Ghana			Kenya			South Africa		
	a	b		a	b		a	b
OLD	0.09	4.02	YOUNG	0.22	-0.75	MALNU	0.45	3.64
YOUNG	0.27	1.20	OLD	0.38	2.51	FOOD	1.75	1.08
PREG	0.25	7.62	DISAB	0.35	4.02	EMPLOY	-0.03	-33.17
DISABLE	0.02	123.67	PASTOR	0.60	3.41	YOUNG	0.76	0.41
ECO	0.87	-0.37	SUBSIS	0.54	1.07	OLD	0.25	3.18
SHELTER	1.19	0.75	SHELTER	4.88	0.04	PREGN	0.23	7.40
WATER	1.45	0.72	SANIT	1.31	0.50	DISABLE	0.23	7.05
SANIT	0.72	-0.17	WATER	0.70	1.61	WATER	0.55	2.26
INFOR	0.44	2.14	INFOR	0.69	2.27	SANIT	0.57	1.35
MALNU	0.23	4.20	FOOD	0.50	-0.84	SHELTER	-0.04	-25.42
FOOD	0.58	0.92	MALNU	0.30	4.60	INFOR	0.10	19.19
			INFOEMP	-0.18	-6.70			

Test of validity

Because the climate vulnerability indicators were drawn from existing literature (see Section 1.2), they all demonstrate a high level of face validity. The following sections focus on the criterion validity (i.e., relations with other variables).

The criterion validity test concerns the relations between the vulnerability indicators with other variables that are highly correlated with climate vulnerability. In this paper, we focused on two variables: whether the household is considered poor and the geographic location of the household (rural vs urban). We have seen that there are large gaps of multidimensional vulnerability measures between urban and rural areas, and poverty status across the three countries.

Table 4 shows the logistic regression analysis results. Columns 3-5 show the logistic regression coefficient b together with its standard error and significance level, when the predictor was the geographic location of the household (urban = 1; rural = 0). Likewise, columns 6-8 shows the coefficient b, standard error and significance level, when the predictor was the overall poverty condition of the household (non-poor = 0; poor = 1). As shown, being in the rural area and in poor households were predictive (and significant at $p < .005$) of most of the climate vulnerability indicators across the three countries. The results, therefore, indicated that the climate vulnerability indicators demonstrate a high level of criterion validity.

Table 4: Logistic Regressions of the Climate Vulnerability Indicators as a Function of Poor Households and Living in Rural Areas

Ghana		Geographic Location (rural = 0; urban = 1)			Poor Household (non-poor = 0; poor = 1)		
	Variables	b	SE	sig.	b	SE	sig.
	Old People	**-0.17**	**0.07**	**0.02**	0.51	0.07	0.00
	Young People	**-0.54**	**0.07**	**0.00**	-0.12	0.07	0.09
	Pregnant Women	**-0.89**	**0.20**	**0.00**	-0.17	0.17	0.33
	Disability	-0.14	0.31	0.65	0.19	0.29	0.52
	Vulnerable Employment	**-1.68**	**0.08**	**0.00**	**0.57**	**0.09**	**0.00**
	Unimproved Shelter	**-1.31**	**0.09**	**0.00**	**0.57**	**0.09**	**0.00**
	Unimproved Water	**-1.98**	**0.10**	**0.00**	**0.57**	**0.09**	**0.00**
	Unimproved Sanitation	**-1.24**	**0.07**	**0.00**	**0.57**	**0.09**	**0.00**
	Information Deprivation	-0.19	0.11	0.09	**0.57**	**0.09**	**0.00**
	Malnutrition	**-0.23**	**0.09**	**0.01**	**0.57**	**0.09**	**0.00**
	Food Deprivation	**-0.59**	**0.08**	**0.00**	**0.57**	**0.09**	**0.00**
Kenya							
	Old People	**-0.71**	**0.04**	**0.00**	**0.41**	**0.03**	**0.00**
	Unimproved Water	**-1.28**	**0.04**	**0.00**	**0.46**	**0.04**	**0.00**
	Unimproved Shelter	**-1.47**	**0.03**	**0.00**	**0.90**	**0.03**	**0.00**
	Food Deprivation	**-0.43**	**0.03**	**0.00**	**1.09**	**0.04**	**0.00**
	Unimproved Sanitation	**-1.93**	**0.03**	**0.00**	**1.38**	**0.04**	**0.00**
	Young People	**-0.52**	**0.03**	**0.00**	**0.73**	**0.03**	**0.00**
	Disability	**-0.45**	**0.05**	**0.00**	**0.45**	**0.05**	**0.00**
	Pastoralist Households	**-2.49**	**0.11**	**0.00**	**1.20**	**0.05**	**0.00**
	Subsistence Households	**-1.46**	**0.03**	**0.00**	**-0.11**	**0.03**	**0.00**
	Information Deprivation	**-0.89**	**0.05**	**0.00**	**1.00**	**0.04**	**0.00**
	Malnutrition	**-0.67**	**0.05**	**0.00**	**0.55**	**0.05**	**0.00**
South Africa							
	Malnutrition	-0.10	0.10	0.31	**1.35**	**0.11**	**0.00**
	Food Deprivation	**-1.00**	**0.08**	**0.00**	**2.80**	**0.08**	**0.00**
	Vulnerable Employment	**-0.56**	**0.07**	**0.00**	**-0.63**	**0.08**	**0.00**
	Young People	**-0.23**	**0.06**	**0.00**	**1.52**	**0.06**	**0.00**
	Old People	**-0.59**	**0.06**	**0.00**	0.03	0.06	0.63
	Pregnant Women	**-0.23**	**0.12**	**0.05**	**0.42**	**0.12**	**0.00**
	Disability	-0.12	0.10	0.25	**0.39**	**0.10**	**0.00**
	Unimproved Water	**-2.82**	**0.11**	**0.00**	**0.65**	**0.08**	**0.00**
	Unimproved Sanitation	**-2.02**	**0.07**	**0.00**	**0.52**	**0.07**	**0.00**
	Unimproved Shelter	**1.34**	**0.11**	**0.00**	**0.39**	**0.09**	**0.00**
	Information Deprivation	-0.06	0.16	0.69	**0.61**	**0.16**	**0.00**

Notes: 1. ** $p < .001$ * $p < .05$

Discussion & Conclusion

Together, our results suggest that the vulnerability indicators are multidimensional. Some are more reliable and valid in one context than in the other. Nevertheless, most of them were significantly associated with being in poor or residence in rural communities.

In **Table 5**, we summarise the psychometric properties of each vulnerability indicator based on their IRT discrimination and relationship with other variables (urban/rural residence and poor/non-poor). Column 1 shows the results of the IRT discrimination values. An indicator was considered as “not effective” in reflecting different levels of climate vulnerability if the discrimination value was below 0 (and correspondingly, the ICC did not follow the expected direction). Also, we examined the relations of these indicators to the two variables associated with climate vulnerability, i.e., household location (urban or rural) and poor/not poor households. All the indicators were a significant function of at least one of these two variables (except “disability” which was not a significant predictor of either variable in Ghana).

Overall, the results demonstrated that “unimproved water” “unimproved sanitation” and “food deprivation” were reliable and valid climate vulnerability indicators across the three countries.

Table 5 Summary of climate vulnerability indicators according to reliability and validity tests across the three countries

	Ghana		Kenya		South Africa	
Vulnerability Indicators	**IRT discrimination**	**Relationship with other variables**	**IRT discrimination**	**Relationship with other variables**	**IRT discrimination**	**Relationship with other variables**
Old People	**EFFECTIVE**	SIG X1	**EFFECTIVE**	**SIG X2**	**EFFECTIVE**	SIG X1
Young People	**EFFECTIVE**	SIG X1	**EFFECTIVE**	**SIG X2**	**EFFECTIVE**	**SIG X2**
Pregnant Women	**EFFECTIVE**	SIG X1	**EFFECTIVE**	**SIG X2**	**EFFECTIVE**	**SIG X2**
Disability	**EFFECTIVE**	SIG X0	**EFFECTIVE**	**SIG X2**	**EFFECTIVE**	SIG X1
Vulnerable Employment	**EFFECTIVE**	**SIG X2**	NOT EFFECTIVE	**SIG X2**	NOT EFFECTIVE	**SIG X2**
Unimproved Shelter	**EFFECTIVE**	**SIG X2**	**EFFECTIVE**	**SIG X2**	NOT EFFECTIVE	**SIG X2**
Unimproved Water	**EFFECTIVE**	**SIG X2**	**EFFECTIVE**	**SIG X2**	**EFFECTIVE**	**SIG X2**
Unimproved Sanitation	**EFFECTIVE**	**SIG X2**	**EFFECTIVE**	**SIG X2**	**EFFECTIVE**	**SIG X2**
Information Deprivation	**EFFECTIVE**	SIG X1	**EFFECTIVE**	**SIG X2**	**EFFECTIVE**	SIG X1
Malnutrition	**EFFECTIVE**	**SIG X2**	**EFFECTIVE**	**SIG X2**	**EFFECTIVE**	SIG X1
Food Deprivation	**EFFECTIVE**	**SIG X2**	**EFFECTIVE**	**SIG X2**	**EFFECTIVE**	**SIG X2**
Pastoralist Households			**EFFECTIVE**	**SIG X2**		
Subsistence Households			**EFFECTIVE**	**SIG X2**		

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