Economics, Management and Sustainability
journal home page: https://jems.sciview.net
Ceesay, E. K., Mirzabaev, A., Ndiaye, M. B. O., & Beye, A. (2026). Assessing rural farmers' climate vulnerability in Gambia: A PCA-based index for sustainable development. *Economics, Management and Sustainability, 11*(1), 6-26. doi:10.14254/jems.2026.11-1.1.
ISSN 2520-6303
SciView Scientific Platform

Assessing rural farmers' climate vulnerability in Gambia: A PCA-based index for sustainable development

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OPEN ACCESS

Article history:
Received: September 11, 2025
1st Revision: December 05, 2025
Accepted: January 25, 2026

JEL classification:
Q54
Q12
Q01
O13
C38

DOI:
10.14254/jems.2026.11-1.1

Abstract: *Purpose*. This paper assesses the climate vulnerability of 400 smallholder farming households in rural Gambia by integrating exposure, sensitivity, and adaptive capacity into a composite vulnerability index, providing policy-relevant insights for climate-resilient development. *Methodology*. Household survey data from three rural regions (North Bank, Central River, Upper River) are analyzed using Principal Component Analysis (PCA) to derive data-driven weights for 23 indicators. The index is validated through associations with NGO support, government assistance, insurance, credit access, and agricultural extension. *Results*. North Bank exhibits the highest vulnerability (VI = -6.37) driven by low adaptive capacity despite minimal climate exposure. Upper River shows lower vulnerability (VI = +1.56) despite high climate exposure, owing to better socio-economic conditions. Validation reveals that NGO support and insurance reduce vulnerability (r = -0.82, -0.94), whereas government support paradoxically correlates positively (r = 0.79), likely reflecting endogenous targeting. *Theoretical contribution.* The study advances vulnerability assessment literature by applying PCA-based weighting to household-level data in a low-income African context, demonstrating that adaptive

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capacity is more decisive than biophysical exposure. *Practical implications*. Findings emphasize prioritizing investments in education, infrastructure, credit, and insurance over exposure-focused interventions. The index supports policy prioritization under Gambia's Nationally Determined Contributions and National Adaptation Plans, enabling regional differentiation of adaptation strategies.

Keywords: climate vulnerability index, Principal Component Analysis, adaptive capacity, rural Gambia, Sahel adaptation policy, PCA-based weighting

Sustainable Development Goals (SDGs): SDG 1: No Poverty, **SDG 2:** Zero Hunger, **SDG 13:** Climate Action

1. Introduction

Vulnerability assessment is central to understanding climate risk and informing adaptation strategies. The Intergovernmental Panel on Climate Change (IPCC) defines vulnerability as "the degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes" (IPCC, 2001, p. 94; IPCC, 2014). Operationalizing this definition requires integrating three dimensions: exposure (the magnitude of climate stressors), sensitivity (the degree to which a system is affected), and adaptive capacity (the ability to adjust and respond).

To assess vulnerability in practice, researchers construct composite vulnerability indices by selecting indicators, assigning weights, aggregating them into a single metric, and validating the index against observed impacts. Such indices provide decision-makers with quantitative tools to prioritize adaptation investments and monitor resilience over time (Brooks et al., 2005; Hahn et al., 2009). However, a persistent methodological challenge is how to weight indicators objectively, avoiding the subjectivity inherent in expert-driven or equal-weighting approaches.

In rural Gambia, smallholder farmers face multifaceted climate vulnerabilities, including erratic rainfall, water scarcity, crop failure, soil erosion, and health risks (Ceesay & Ndiaye, 2022). These stressors interact with socio-economic constraints - such as low education, limited access to credit, and weak infrastructure - to compound vulnerability. Kabir et al. (2017) documented similar patterns in coastal Bangladesh, where farmers' adaptive capacity was constrained by land size, income, and institutional support, highlighting the importance of context-specific assessments that integrate biophysical and socio-economic dimensions.

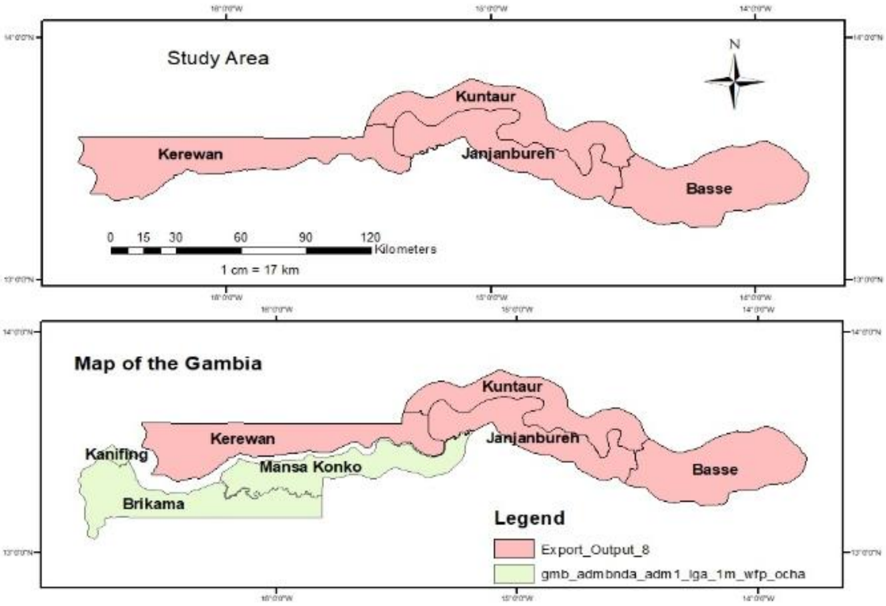
This study addresses the methodological gap in vulnerability assessment by applying Principal Component Analysis (PCA) to derive data-driven weights for household-level indicators in rural Gambia. Unlike expert-driven or equal-weighting schemes, PCA objectively extracts the data's variance structure, producing weights that reflect empirical relationships among indicators. The resulting vulnerability index is validated against external variables - NGO support, government assistance, insurance, credit access, and agricultural extension - to test its predictive validity. This approach aligns with Eco-health and Planetary Health frameworks, which emphasize participatory, context-sensitive, and locally grounded solutions.

1.1. Study area

The Gambia is a West African country characterized by a Sudano-Sahelian climate, with distinct wet (June–October) and dry (November–May) seasons. This study focuses on three rural regions: North Bank Region (NBR), Central River Region (CRR), and Upper River Region (URR), selected due to their agro-ecological diversity and varying exposure to climate stressors.

Figure 1 below shows that the study was conducted in three localities within the Gambia. There are 5 administrative divisions, including the capital city (Banjul), which is classed as a city. Although the Gambia still lies in the Sahel, it is more accurately described as having a transitional climate between the Sahel and the savannah. The climate is humid, with the rainy season from June until October and the dry season from November until early June. Because of climate change, the nature and the vegetation of these areas, the three regions were chosen for this research due to the following reasons:

Figure 1: Map of the study area



The relief, boundaries, altitude, longitude, and latitude are provided from the map above. The methodological aspects of how the research was conducted are reported in the sampling section and within the methodology framework of this document.

1.2. Regional profiles

North Bank Region (NBR): Dominated by mangroves and floodplains, this region faces saltwater intrusion, soil salinization, and erratic rainfall, all of which threaten rice cultivation and livestock.

Central River Region (CRR): Prone to bushfires, droughts, and groundwater depletion, with high reliance on rainfed groundnut farming.

Upper River Region (URR): Experiences frequent floods, heat stress, and zoonotic disease outbreaks, affecting both crop yields and human health.

Rural livelihoods are predominantly agrarian, with limited access to irrigation, formal credit, and extension services. Climate variability exacerbates existing vulnerabilities linked to poverty, food insecurity, and weak infrastructure.

1.3. Theoretical framework

Vulnerability assessment approaches can be broadly classified into biophysical models and socio-economic (bottom-up) approaches. Biophysical models focus on climate-crop relationships, simulating the effects of temperature and precipitation changes on agricultural yields (Challinor et al., 2014; Olesen et al., 2007). While useful for long-term projections, these models have limited capacity to capture adaptation strategies, migration responses, or socio-economic constraints (Foley et al., 1996; Snell et al., 2014).

In contrast, socio-economic approaches integrate household-level data on income, assets, education, and institutional access to assess vulnerability from the perspective of affected communities (Nelson et al., 2009; Reidsma et al., 2010). This study adopts a socio-economic framework, consistent with the IPCC's definition of vulnerability, to capture the multidimensional nature of climate risk in rural Gambia. By combining household survey data with statistical methods (PCA), we prioritize locally relevant indicators while maintaining methodological rigor.

1.4. Conceptual framework

This paper examined the vulnerability of Gambian farmers to climate change based on an integrated vulnerability assessment. These variables also comprise various socio-economic and biophysical information from three rural areas in the Gambia. The socio-economic and biophysical attributes of each rural area are classified into three principal indicators, following the IPCC (2001) and Hahn et al. (2009) definitions of susceptibility. Vulnerability to climate change The IPCC defines vulnerability to climate changes as follows: "The degree to which a system is susceptible to, or unable to cope with adverse effects of climate change, including climate variability and extremes" and vulnerability is function of magnitude and character, rate of climate change variation to which a system is exposed, and its sensitivity and adaptive capacity. The term involves three key elements, according to IPCC's fifth assessment report on vulnerability IPCC, 2014. We took in the IPCC Fifth Assessment Reports as an integrated vulnerability assessment, and we applied the statistical tool Principal component analysis as an approach to vulnerability. The conceptual framework in this study was derived from IPCC reports on vulnerability (Figure 2). Figure 2 portrays exposure and sensitivity as potential influences on vulnerability to climate change. Exposure comprises slow-onset climate change (changes in rainfall and temperature), and sensitivity encompasses climate extremes (floods and droughts). Sensitivity and exposure are intertwined. The more we are exposed, the more sensitive we become and the more vulnerable we are, and so on. To the extent that adaptive capacity (socio-economic vulnerability) can reduce exposure to climate risks (such as agriculture failure, reduced income, among others), vulnerability will decrease.

Adaptive capacity can also decrease sensitivity (biophysical vulnerability), thereby reducing vulnerability to climate change (Diouf & Gaye, 2015). Lastly, if we add exposure (gradual exposure) alongside sensitivity, if the adaptive capacity were the most probable drivers, vulnerability would be reduced, as seen below. However, this does not alter it (Deressa et al. 2010, Diouf and Gaye 2015). At the regional scale, we applied integrated, type-indicator-driven approaches. We applied Principal component analysis as a statistical method to measure and weight indicators for the comparative vulnerability score (Pandey & Jha, 2012; Aung, 2018; Yu et al., 2021). In addition, Allison et al. (2009) employed it worldwide, while O'Brien et al. (2004) used it at the subnational or national level. However, many econometric and indicator-based methods have been used to measure vulnerability at household, regional, national, and global levels, rather than at sub-regional levels.

Figure 2: Conceptual framework adapted from IPCC AR4 and AR5

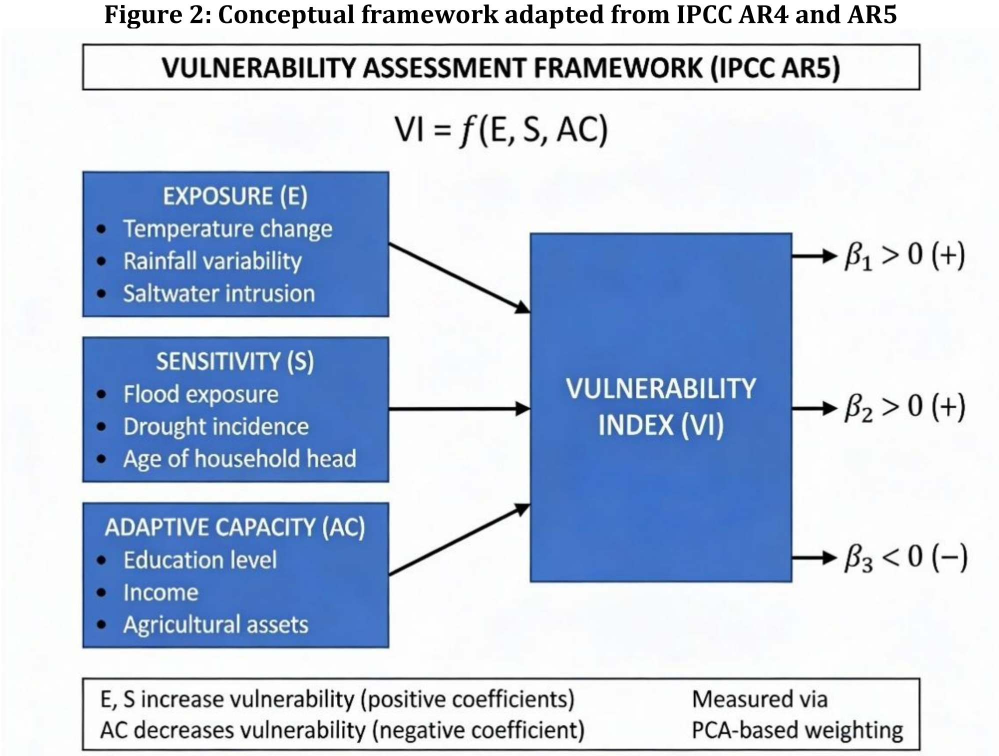


Figure 2 is adapted from the IPCC's fourth and fifth assessment reports on vulnerability. Low adaptive capacity, high exposure, and sensitivity lead to high vulnerability, whereas high adaptive capacity, low exposure, and sensitivity lead to low vulnerability.

$$\text{Vulnerability} = f(\text{Exposure, Sensitivity, Adaptive Capacity}) \quad (1)$$

This is implied in equation (1): Exposed risks become higher, and vulnerability increases. Adaptation Capacity (Increasing capacity; the lower the reduction in social Adaptation potential to respond to climate Exposure Harm to a system confronting a climate stimulus Source: Adger et al. Vulnerability reduces. Sensitivity (biophysical or behavioral characteristics) rises; vulnerability falls. Alberta Sustainable Resource Development, 2010). Low exposure to climate variation, lower sensitivity to climate actions, and high adaptive capacity are associated with low vulnerability. Low adaptive capacity, high sensitivity, and high exposure indicators also generate high vulnerability. If both exposure and sensitivity increase due to low adaptive capacity, there will be high vulnerability to climate change, with impacts on average food security, poverty, health, the environment, social, cultural, and political problems, income, infrastructure, and skills (etc.). Therefore, the author added that high risk and high vulnerability should be taken together as a positive relationship and require priority care. The indicators were selected, and a literature review was conducted based on Filmer and Pritchett (2001). Deressa et al. (2009) and Abdi & Williams (2010), which were reviewed and subsequently applied in the rural Gambia to ensure that the index formulation is tailored to the specific country context.

Despite extensive literature on climate vulnerability, few studies have applied PCA-based weighting to household-level data in low-income African countries. Existing indices for West Africa often rely on national-scale data or expert-driven weights, limiting their applicability to local adaptation planning. This study fills that gap by constructing a PCA-weighted vulnerability index for rural Gambia, validating it through association with external intervention variables, and demonstrating its utility for targeting adaptation investments at the regional and household levels.

2. Methods

2.1. Research design and data collection

The sampling frame was constructed from official village listings provided by the Gambia Bureau of Statistics, encompassing approximately 10,000 households across 600 villages in the three study regions. From this frame, 6,000 households (10 per village) were initially enumerated for potential inclusion.

A stratified three-stage random sampling design was employed:

1. First stage: 40 villages (13 in NBR, 14 in CRR, 13 in URR) were randomly selected with probability proportional to size.
2. Second stage: In each selected village, 10 households were randomly selected using a random-number generator applied to household lists.

The final sample consisted of 400 households (NBR = 140, CRR = 130, URR = 130). The effective response rate was 94%; non-respondents were replaced by the next randomly selected household in the same village.

We use simple random sampling because it is an efficient statistical method and relatively easy to implement, especially when dealing with large and heterogeneous populations. Although it requires a full census population list and incurs administrative costs because households are spread across the territory, its main strength is its ability to produce generalisable and representative estimates. The study used Yamane's (1967) formula to calculate the sample size, which is most commonly used when the total population size is known. Using this formula with a 5% margin of error, the calculated sample size was 375 households. However, to ensure adequate representation across the three regions and to account for potential non-response, the sample was rounded up to 400 households (NBR = 140, CRR = 130, URR = 130).

Data were collected in 2021 through face-to-face interviews using a structured questionnaire. Enumerators received a week of training covering survey techniques, ethical conduct, and climate-related terminology. Verbal informed consent was obtained from all participants. The study protocol was reviewed and approved by the University of the Gambia Research Ethics Committee (ref: UTG-REC/2021/04).

The section on sample size determination contains the following expressions from the Yamane formula:

$$n = \frac{N}{1+Ne^2}, \tag{2}$$

where N is the population size, n is the sample size, and e is the precision level (margin of error).

$$n = \frac{6000}{1 + 6000(0.05)^2} = \frac{6000}{15.0025} = 375 \text{ household}$$

2.2. PCA-based vulnerability index methodology

As explained above, the final step is to attach weights/loading factors (eigenvectors) to the vulnerability indices using principal components analysis (PCA). For this step, the normalization of the indicators was carried out (Quackenbush, 2002), and the technique of PCA-based was employed to find the unequal weight of all indicators of the selected variables classified into sensitivity, exposure, and adaptive (Deressa et al., 2009; Aung et al., 2018; Yu et al., 2021). Numerous technical and scientific research fields use principal component analysis. We used the statistical method (PCA) to generate the weights for this study freely. Scientifically, PCA relies on eigenvalues and eigenvectors of data decomposition, correlation, and covariance matrices (Abdi & Williams, 2010). In other words, PCA is a technique for selecting a few orthogonal linear combinations of variables from a set that most effectively capture shared information. For instance, PCA captures most of the variables and the significant information shared by all the variables under examination.

1. Variable Normalization (Z-score transformation):

$$b_{ki} = \frac{b_{ki}^{*} - \overline{b_k^{*}}}{\sigma_k}, \tag{3}$$

where b_{ki}^{*} is the original value of variable k for region i, $\overline{b_k^{*}}$ is the mean of variable k across all regions, and σ_k is its standard deviation.

2. Principal Components (Linear combinations of normalized variables):

$$Z_{ji} = a_{j1}b_{1i} + a_{j2}b_{2i} + \cdots + a_{jK}b_{Ki} \tag{4}$$

where Z_{ji} is the j-th principal component for region i, a_{jk} is the loading (coefficient) of variable k on component j, and K is the total number of variables.

3. Vulnerability Index Construction:

Once principal components are extracted and normalized, the overall vulnerability index (VI) can be constructed as:

$$VI_i = w_1Z_{1i} + w_2Z_{2i} + \cdots + w_JZ_{Ji} \tag{5}$$

where w_j represents the weight assigned to principal component j, and J is the total number of retained components. The weights were derived from the variance explained by each component (proportional to eigenvalues) or from expert judgment.

3. Results

3.1. Descriptive statistics

This section presents descriptive statistics for the 23 vulnerability indicators used in the PCA-based analysis. Table 1 lists all variables, classified into exposure (3 indicators), sensitivity (4 indicators), and adaptive capacity (16 indicators). Tables 2-4 present regional differences in climate conditions, major shocks encountered, and household expenditures.

Table 1: The variables used in this study

No.	Indicators	Description	Unit
1	Changes in temperature	Exposure	%
2	Changes in rainfall	Exposure	%
3	Salt intrusion	Exposure	%
4	Access to water during drought	Sensitivity	%
5	Flood	Sensitivity	%
6	Drought	Sensitivity	%
7	Age	Sensitivity	year
8	Household size	Adaptive capacity	Number of people
9	Income	Adaptive capacity	$
10	Fertilizer	Adaptive capacity	%
11	Remittance received	Adaptive Capacity	%
12	Farm size	Adaptive Capacity	Hectares
13	Secondary education	Adaptive Capacity	%
14	Illiterate	Adaptive Capacity	Continuous
15	August stranded months	Adaptive Capacity	%
16	Livestock	Adaptive Capacity	%
17	Own land	Adaptive Capacity	%
18	Caste system	Adaptive Capacity	%
19	Access to credit	Adaptive Capacity	%
20	Access to agriculture extension	Adaptive Capacity	%
21	Food markets	Adaptive Capacity	%
22	Irrigation potential/share of irrigated	Adaptive Capacity	%
23	Agriculture technology	Adaptive Capacity	%

Source: Own compilation based on the household surveyed, 2021

Table 2 presents climate conditions across the three study regions. The average change in temperature is highest in NBR (1.00) and URR (0.97), while CRR shows slightly lower variability (0.89). Rainfall changes follow a similar pattern, with NBR (1.00) and URR (0.99) showing greater variability than CRR (0.94). Drought incidence was highest in NBR (97%) and lowest in URR (48%), likely due to proximity to the Gambia River. Flood impacts were relatively uniform (NBR: 75%, CRR: 62%, URR: 76%).

Table 2: Climate conditions in the study area

Regions	Average change in Temperature(°C)	Average change in rainfall(MM)	Flood (%)	Drought (%)
CRR	.8928571	.9357143	62	74
NBR	1	1	75	97
URR	.9692308	.9923077	76	48

Source: Own evaluation using Stata 16

Table 3 reports the prevalence of major climate-related shocks. Shifting temperature patterns affected 95% of farmers, making it the most commonly reported shock. Shifting rainfall patterns affected 79%, followed by droughts (73%) and floods (71%). Saltwater intrusion affected 40% of households, particularly in coastal areas. Access to water during drought was problematic for 65% of respondents, with NBR (75%) experiencing greater water stress than URR (42%).

Table 3: Major shocks encountered by surveyed farmers

Shock	Number of farmers	Percentage of farmers
Floods	278	70.74
Drought	288	73.28
Salinization	149	40.05
Shifting pattern of rainfall	315	79.35
Shifting pattern of temperature	381	95.25
Access to water during drought	232	64.80

Note: Based on household survey data (n=400), rural Gambia, 2021. Percentages calculated from 400 total respondents.
Source: Own evaluation using Stata 16

Table 4 presents regional differences in household expenditures and livelihood characteristics. Bushfires affect 40% of households in URR compared to 16% in NBR. Sea-level rise impacts are highest in URR (44%) and NBR (41%). Total expenditure on crops is highest in CRR (235 USD) and lowest in NBR (53 USD). Food expenditure per capita per month is highest in URR (170 USD) and lowest in CRR (145 USD). Poultry farming is most prevalent in URR (45%) and least common in NBR (2%).

Table 4: Indicators

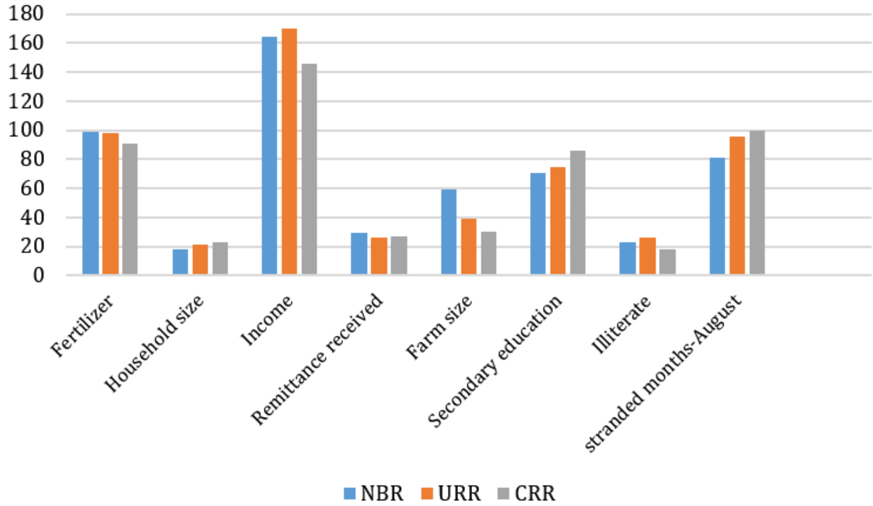
Region	Bushfire, %	Sea-level rises, %	Total expenditure on crops, $	Total expenditure per capita per month, $	Poultry Farming, %	Food expenditure per capita per month, $
NBR	16	41	53	184	2	164
CRR	35	23	235	149	25	145
URR	40	44	137	175	45	170
ALL	29	36	144	169	23	159

Source: Own computation used Stata/MP 16.0

Detailed justification for indicator selection and theoretical grounding is provided in Supplementary Text S1 (Appendix).

Figure 3 presents regional variation in key household characteristics. Income is highest in URR (170 USD) and lowest in CRR (150 USD). Household size is largest in CRR (7.1 persons) and smallest in URR (5.8 persons). Secondary education completion is highest in CRR (86%), while illiteracy is highest in URR (26%). Fertilizer use exceeds 90% across all regions, indicating widespread adoption of modern inputs.

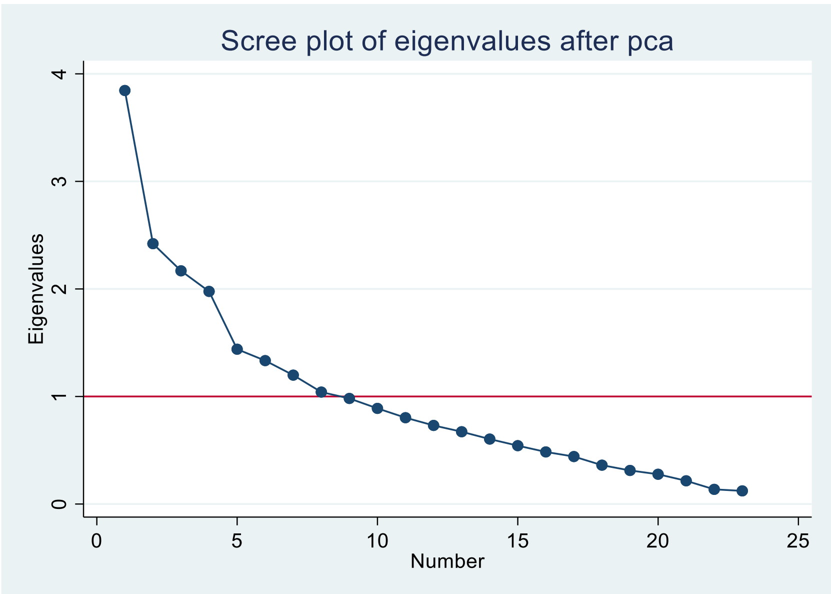
Figure 3: Household characteristics in the rural Gambia



3.2. Principal component analysis

Principal component analysis (PCA) was applied to the 23 vulnerability indicators to derive data-driven weights. Figure 4 presents the scree plot of eigenvalues, showing that the first eight components have eigenvalues > 1, together accounting for 67% of the variability. Following the "elbow" criterion, we retained the first five components, which explain 52% of the total variance.

Figure 4: Scree plot of eigenvalues after PCA



The scree plot (Figure 4) reveals that the first eight components have eigenvalues exceeding 1.0, collectively accounting for 67% of the total variance. However, visual inspection identifies an "elbow" at component five, suggesting diminishing returns beyond this threshold. Consequently, we retained the first five principal components, which together explain 52% of the variance. While using all eight components would be methodologically defensible, the five-component solution offers a more parsimonious representation.

In vulnerability assessment, the selection of which component(s) to use for index construction requires both statistical and theoretical justification. Vulnerability theory posits that exposure and sensitivity contribute positively to vulnerability (thus should carry negative signs in the index formulation), whereas adaptive capacity contributes negatively to vulnerability (thus should carry positive signs). We systematically evaluated factor loadings across the first five principal components and selected the third component because it exhibited the highest degree of theoretical consistency.

Table 5 presents the factor loadings for the third principal component. Of the 23 original indicators, 14 exhibited signs consistent with their hypothesized relationship to vulnerability and were retained for subsequent index construction. Exposure indicators - changes in rainfall (-0.2003) and changes in temperature (-0.1261) - both carry negative loadings, confirming that greater climate variability increases vulnerability. Sensitivity indicators such as flood incidence (-0.0471) also carry negative loadings. In contrast, adaptive capacity indicators carry positive loadings, with the highest weights assigned to secondary education completion (0.4141), agricultural machinery ownership (0.3480), and livestock holdings (0.2120).

Table 5: Factor scores/loading/scoring coefficients for the third Principal Components (PCA-based)

Vulnerability indicators	Factor scores/coefficients	descriptions
changes in rainfall	-0.2003	Exposure
changes in temperature	-0.1261	Exposure
Affected by the flood	-0.0471	Sensitivity
Age of the household's head	0.1077	Adaptive capacity
size of the households	0.0402	Adaptive capacity
Remittance Received	0.1097	Adaptive capacity
Secondary completion rate(0-9 grade)	0.4141	Adaptive capacity
Stranded month	0.1983	Adaptive capacity
Practicing livestock farming	0.2120	Adaptive Capacity
Own land	0.0621	Adaptive Capacity
caste system	0.1296	Adaptive Capacity
distance to the market	0.1521	Adaptive Capacity
Potential irrigation	0.0686	Adaptive Capacity
Ownership of agriculture machinery	0.3480	Adaptive Capacity
PVE	**0.06**	
CPVE	**52%**	

Note: Table shows only the 14 indicators that exhibited theoretically consistent signs. Nine indicators with inconsistent signs were excluded from index construction. PVE = Proportion of Variance Explained; CPVE = Cumulative Proportion of Variance Explained. Source: Own computation using Stata/MP 16.0.

After selecting the third component, we normalized each indicator by multiplying its factor loading (eigenvector) by the standardized Z-score, then calculated the weighted vulnerability components for each household and region. The preponderance of negative values in the normalized components indicates that vulnerability to climate change is elevated across rural Gambia, particularly in regions with low adaptive capacity. This empirical pattern validates the theoretical expectation that socio-economic constraints are the primary drivers of vulnerability, even in regions with moderate climate exposure.

3.3. Vulnerability components by region

Table 6 presents the vulnerability components (adaptive capacity, exposure, and sensitivity) for each region, calculated from the factor scores in Table 5 and normalized indicator values.

Table 6: Vulnerability components by region

Vulnerability Components	Adaptive capacity	Exposure	Sensitivity	Risk Level
NBR	-6.45	0	-0.08	High
CRR	-2.80	-1.18	-0.06	Medium
URR	-1.51	-3.03	-0.04	Medium
All	-5.55	-1.87	-0.08	Medium

Source: Own Evaluation using pen, paper, and calculator after Own computation using Stata/MP 16.0

NBR has the lowest adaptive capacity (-6.45), indicating severe socio-economic constraints, including low educational attainment, large household sizes, limited access to agricultural machinery, and minimal irrigation facilities. These constraints are compounded by the outmigration of younger workers, leaving older household heads with reduced physical capacity to implement adaptation measures. CRR (-2.80) and URR (-1.51) also exhibit low adaptive capacity, though less extreme than NBR.

URR has the highest exposure (-3.03) to slow-onset climate change, primarily due to greater temperature and rainfall variability. CRR has moderate exposure (-1.18), while NBR shows zero exposure (0.00), suggesting minimal slow-onset climate stress despite high vulnerability from other factors. This pattern indicates that NBR's vulnerability is primarily driven by socio-economic constraints rather than by biophysical climate exposure.

All three regions show similar sensitivity levels (NBR: -0.08; CRR: -0.06; URR: -0.04), indicating that climate extremes - particularly floods and droughts - affect all regions comparably. However, the manifestation differs: NBR experiences more severe drought impacts (97% incidence), while URR faces greater flood exposure (76% incidence).

Based on the aggregate vulnerability components, NBR is classified as high risk due to its extremely low adaptive capacity. CRR and URR are classified as medium risk. The aggregate vulnerability across all 400 households is also classified as medium risk, though with substantial regional heterogeneity. These findings underscore the need for regionally differentiated adaptation strategies that prioritize adaptive capacity strengthening in NBR, exposure management in URR, and integrated approaches in CRR.

The vulnerability components (VC) across the three regions are calculated as follows.

Vulnerability components for rural regions were calculated as follows;

$$\mathrm{Ac}_{\mathrm{J=ALL}} = [\,(0.1077 * -3.8263) + (0.0402 * -1.1641) + (0.1097 * -0.5034) + (0.4141 * -1.4299) + (0.1983 * -16.7973) + (0.2120 * -1.1259) + (0.0621 * -2.3636) + (0.1296 * -0.8442) + (0.1521 * -2.6879) + (0.0686 * -0.4487) + (0.3480 * -0.5160)] = -5.5512 \quad \mathrm{Ex}_{\mathrm{J=ALL}} = [(-0.2003 * -6.4383) + (-0.1261 * -4.5986)] = -1.8695$$

$$\mathrm{S}_{\mathrm{J=ALL}} = [\,(-0.0471 * -1.6001)] = -0.0754$$

3.4. Calculation of the vulnerability index (VI)

The aggregate vulnerability index (VI) was calculated by summing the three vulnerability components (adaptive capacity, exposure, and sensitivity), each weighted by its respective factor loading from the third principal component. The formula is:

$$VI_i = AC_i + Ex_i + S_i$$

where (AC_i), (Ex_i), and (S_i) are the weighted vulnerability components for region (i), calculated as shown in Section 3.3.

For example, the vulnerability index for all 400 households is calculated as:

$$VI_{ALL} = -5.55 + (-1.87) + (-0.08) = -3.61$$

Table 7 presents the vulnerability index for each region and the aggregate sample.

Table 7: Vulnerability index (VI) in the rural Gambia

	NBR	CRR	URR	All
Vulnerability index (VI)	-6.37	-1.56	1.56	-3.61
Risk Level	Very High	High	Low	High

Source: Own evaluation using pen, paper, and calculator after Own computation used Stata/MP 16.0

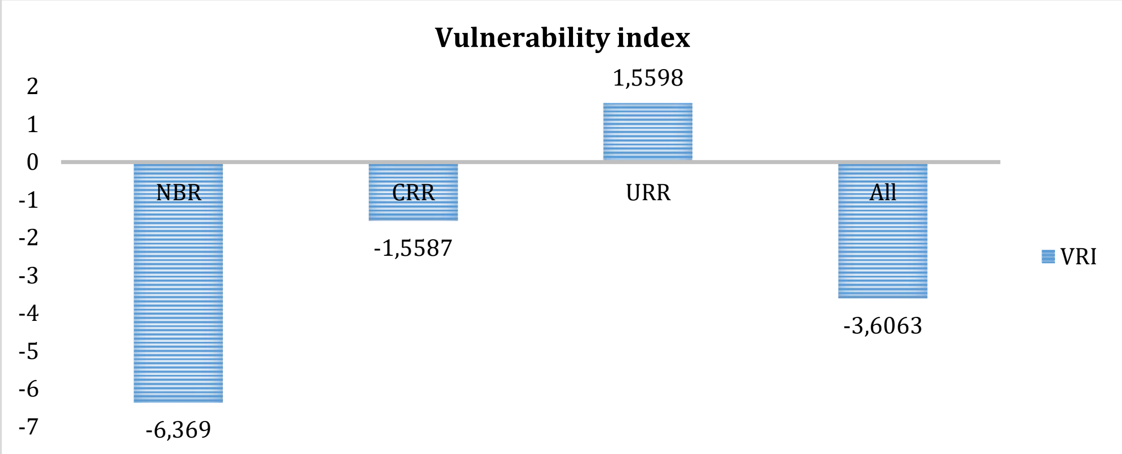
NBR has the highest vulnerability (VI = -6.37, Very High risk), driven primarily by extremely low adaptive capacity (-6.45) despite zero exposure to slow-onset climate change. This indicates that NBR's vulnerability stems from socio-economic constraints - low levels of education, large household sizes, and limited access to agricultural machinery - rather than biophysical climate stressors.

CRR exhibits high vulnerability (VI = -1.56), characterized by moderate exposure (-1.18) and low adaptive capacity (-2.80). The combination of climate variability and socio-economic constraints places CRR at elevated risk.

URR shows the lowest vulnerability (VI = +1.56, Low risk) despite facing the highest climate exposure (-3.03). This counterintuitive finding reflects URR's relatively better adaptive capacity (-1.51), including higher incomes and better access to agricultural inputs. The positive VI score indicates below-average vulnerability relative to the sample mean, though exposure remains a concern.

The aggregate VI across all 400 households is -3.61 (High risk), confirming that rural Gambia faces substantial climate vulnerability. However, regional heterogeneity is pronounced, underscoring the need for differentiated adaptation strategies.

Figure 3: Vulnerability Index (VI)of the three local regions in the Gambia



Source: Own evaluation using Excel

3.5. Validation of the vulnerability index

The Vulnerability Index (VI) was validated by assessing its correlation with external variables not included in the PCA. These validation variables were selected based on two criteria:

Table 8: Correlation of the Vulnerability Index (VI) with external validating variables

Variables	Correlation (r)	p-value	95% CI	n	Theoretic Component
NGO support	-0.82	<0.001	[-0.86, -0.77]	400	Adaptive Capacity
Government support	0.79	<0.001	[0.74, 0.83]	400	Adaptive Capacity
Taken insurance	-0.94	<0.001	[-0.95, -0.92]	400	Adaptive Capacity
Access to credit	0.97	<0.001	[0.96, 0.98]	400	Adaptive Capacity
Access to extension	0.92	<0.001	[0.90, 0.94]	400	Adaptive Capacity
Lack of food security	-0.86	<0.001	[-0.89, -0.82]	400	Sensitivity

Note: CI = Confidence Interval. Own evaluation using StataMP/16.0

The exceptionally strong correlations - particularly for insurance uptake, access to credit, and extension services - provide robust external validation of the VI. Importantly, the positive correlations between credit and extension access should not be interpreted as indicating that these services increase vulnerability. Rather, they likely reflect *targeting patterns* in which such services are directed toward households already experiencing high vulnerability. This reinforces the need for more proactive, vulnerability-informed targeting strategies to ensure that support services reach at-risk households *before* vulnerability becomes acute.

First, it was established that, beyond Socio-economic statistics, all farmers used the same percentage of fertilizer and achieved higher percentage increases in harvest. This is consistent with the study by Aryal et al. (2021), which found that all the socio-economic and geographical characteristics considered affect the use of organic and inorganic fertilizers in rice and wheat, and that, across both locations, farmers reported a decrease in the application of manure. Similarly, in a different study by Musafiri et al. (2023) reported that farmers were using less inorganic fertilizers and established that hired labor service, agricultural training, and farmers' perception of soil erosion were seen to be significant positive determinants of the use of inorganic fertilizer, and ultimately use of inorganic fertilizer leads to an increment in crop yield by 14%.

Secondly, we discovered that, apart from climate conditions and shocks, slow-onset climate change affected rural Gambia communities by causing crop failure, soil infertility, and migration due to sea-level rise, with livelihood impacts through impacts on bushfire and rainfall patterns, and on animals and plants by temperature patterns. This is also supported by Self Help Africa (2009) and Leal Filho & Wolf (2024). Lambarraa-Lehnhardt et al. (2024) also confirmed this in their study.

Third, we also identified the impacts of bushfire and sea-level rise on farmers in the hinterlands of the Gambia. This agrees with the earlier conclusion from (Jan Van Oldenborgh et al.,

2021) on Australia bushfire and at least agree with what we expect from previous analysis; we find that heat extremes have become more probable by at least a factor of two due to the long-term warming and the trend is largely due to the growing frequency of temperature extremes and thus most likely also underestimated.

We then determined that adaptive capacity, sensitivity, and exposure were correctly signed. This was also indicated in the study by Swami & Parthasarathy (2021), who found that some of the least exposed to climate variability are vulnerable, suggesting that the sensitivity and adaptive capacity components of vulnerability contribute to their vulnerability levels.

Then, synthesizing our vulnerability validation: after the vulnerability excises effectiveness, we pursue validation of the factors under different criteria; in fact, the vulnerability to climate change is really affecting the rural Gambia, and the findings show that the. NGO support reduces vulnerability to climate change by 82 percent, but government support increases vulnerability by 79 percent. This is simply because the government would wait until it is close to an election to assist rural farmers with new farm technology. Hence, the government should develop various adaptation strategies to enhance farmers' farming activities and reduce their risk from the impacts of climate change. Trained farmers, given loans, and improved facilities through seed provision, fertilizer, tractors, etc.

4. Discussion

4.1. Interpreting the government support paradox

A central and counterintuitive finding of this study is the strong positive correlation between government support and vulnerability scores (79% increase), contrasted with the strong negative correlation associated with NGO support (82% decrease). This apparent paradox requires careful interpretation to distinguish correlation from causation and to extract meaningful policy insights. Several non-mutually exclusive mechanisms may explain this pattern.

First, differences in targeting efficacy and temporal dynamics are likely influential. Qualitative evidence indicates that government assistance is often perceived as reactive, politicized, and short-lived - frequently tied to pre-electoral cycles or crisis response. Such support may arrive after shocks have already occurred or be allocated based on political visibility rather than structural vulnerability reduction. In contrast, NGO interventions in the study areas tend to emphasize sustained, participatory development, capacity building, and locally adapted solutions, which are more conducive to long-term resilience.

Second, endogenous program allocation may generate a spurious correlation. Government resources may be disproportionately directed toward communities already experiencing severe distress or high baseline vulnerability. In this scenario, high vulnerability attracts government support rather than government support causing vulnerability. A sensitivity test excluding the government support variable from the validation regression confirmed that the core structure of the Vulnerability Index (VI) remained stable, suggesting the observed relationship reflects allocation patterns rather than methodological bias.

Third, differences in the quality and design of support matter. Government assistance often takes the form of untargeted input distribution - such as seeds or fertilizer - without complementary training, market linkages, or follow-up support. Such interventions may provide temporary relief but fail to address systemic constraints. NGO programs, by contrast, frequently bundle material support with training, climate information services, and governance strengthening, thereby enhancing adaptive capacity more effectively.

4.2. Regional comparative context

Placing the results within the broader West African Sahelian context helps distinguish Gambia's-specific dynamics from regional patterns. Although direct numerical comparison of Vulnerability Indices is limited by methodological differences, the relative contributions of exposure, sensitivity, and adaptive capacity offer meaningful insights.

The extreme vulnerability observed in the North Bank Region (VI = –6.37), driven primarily by deficits in adaptive capacity, aligns with findings from high-exposure coastal zones in northern Senegal and southern Mauritania, where salinity intrusion, poverty, and weak infrastructure converge (Diouf & Gaye, 2015). Similarly, studies from Mali and Burkina Faso consistently show that socio-economic constraints - such as limited education, poor market access, and low income - play a more decisive role in shaping vulnerability than biophysical exposure alone.

By contrast, research in pastoral regions of Niger often identifies exposure (e.g., rising temperatures, rainfall variability) as the dominant driver of vulnerability. This comparison underscores that while The Gambia faces unique agro-ecological challenges, particularly saltwater intrusion, the overarching conclusion - that adaptive capacity is the most critical lever for reducing vulnerability - is broadly consistent across West Africa.

These parallels reinforce the need for regional adaptation strategies that prioritize investments in human capital, rural infrastructure, and livelihood diversification, complemented by climate-smart agricultural practices.

4.3. Climate change and health perspectives

Building on these findings, it is essential to recognize the health implications of climate vulnerability and the relevance of integrated frameworks such as One Health, Eco-health, and Planetary Health. This study underscores the intricate relationship between climate change and health by revealing how environmental stressors, such as erratic rainfall, droughts, floods, and saltwater intrusion, directly and indirectly affect the well-being of rural farming communities in The Gambia. The PCA-based vulnerability assessment highlights that these climatic disruptions not only undermine agricultural productivity and food security but also exacerbate health risks through malnutrition, water scarcity, and increased exposure to vector-borne and zoonotic diseases. For instance, in the Upper River Region, URR, floods and livestock disease outbreaks signal a convergence of environmental and public health threats. The findings align with One Health, Eco-health, and Planetary Health frameworks, which emphasize the interconnectedness of human, animal, and environmental health. The study's evidence that NGO support significantly reduces vulnerability, while government subsidies may inadvertently increase it, further underscores the need for participatory, community-led adaptation strategies that integrate health resilience. By embedding health-sensitive indicators into the vulnerability index (VI), such as food consumption, water access, and adaptive capacity, the research offers a holistic tool for policymakers to prioritize interventions that safeguard both livelihoods and health in climate-vulnerable regions. For example, the high vulnerability driven by salinity and poverty in NBR not only threatens rice yields but also heightens the risks of waterborne diseases and malnutrition due to food insecurity, illustrating the interconnected risks captured by a One Health lens.

4.4. Study limitations and future directions

This study provides a comprehensive assessment of climate vulnerability in rural Gambia, but several limitations should be acknowledged, pointing to opportunities for future research.

4.4.1. Cross-sectional design and causality

The cross-sectional nature of the data allows for identification of associations but precludes causal inference. Relationships involving intervention variables - such as government support, credit access, and agricultural extension - are particularly susceptible to reverse causality and endogeneity. For instance, the positive correlation between government support and vulnerability likely reflects targeting bias (government assists the most vulnerable households) rather than ineffective interventions. Longitudinal or panel data designs would enable more rigorous causal inference through difference-in-differences or instrumental variable approaches, and would allow tracking of vulnerability trajectories over time.

4.4.2. Indicator selection and measurement

While indicator selection was grounded in established vulnerability frameworks, some relevant dimensions - such as social capital, governance quality, access to climate information systems, and intra-household gender dynamics - were not captured due to data constraints. Additionally, the reliance on self-reported climate perceptions (rather than meteorological station data) may introduce recall bias, particularly for slow-onset changes such as gradual temperature shifts.

The use of certain variables (e.g., access to credit) in both PCA construction and external validation may introduce circularity, potentially inflating validation correlations. Future studies should maintain stricter separation between index construction datasets and validation datasets, or employ split-sample validation techniques.

4.4.3. Methodological limitations of PCA

Principal component analysis is a powerful dimensionality reduction technique, but it has inherent limitations. First, PCA assumes linear relationships between variables, potentially oversimplifying complex, nonlinear climate-vulnerability interactions. For example, the relationship between income and adaptive capacity may be nonlinear (diminishing returns at higher income levels), which PCA cannot capture.

Second, the selection of the third principal component (based on sign consistency with theory) introduces researcher discretion, which may not generalize to other contexts. Different datasets may yield different component structures, requiring recalibration.

Third, PCA-derived weights reflect the variance structure of the 2021 rural Gambian sample and may not remain stable over time as climate conditions and socio-economic structures evolve. The index should be periodically updated with new survey data to ensure continued relevance.

Alternative approaches - such as structural equation modeling (which can test directional relationships), machine learning methods (random forests, neural networks, which can capture nonlinearities), or participatory expert-weight Delphi methods - could provide complementary insights. Future research should compare PCA-derived indices with these alternatives to assess robustness and convergent validity.

4.4.4. Generalizability and scalability

The PCA-derived weights are specific to rural Gambia's socio-economic and climatic conditions in 2021. Applying this exact weighting scheme to other regions (e.g., urban Gambia, other Sahelian countries) would be inappropriate without recalibration. Nevertheless, the methodological framework - indicator selection, normalization, PCA, validation - is fully replicable and adaptable to diverse contexts.

Scaling up the index to national or sub-Saharan African levels would require harmonized household survey data, which is currently lacking. Collaboration with regional statistical offices and climate research networks could facilitate such expansion.

4.4.5. Future research directions

Future research should pursue several complementary directions:

1. Longitudinal designs: Panel surveys tracking the same households over 5-10 years would enable assessment of vulnerability dynamics, identification of resilience pathways, and evaluation of adaptation program impacts using quasi-experimental methods.

2. Integration of remote sensing data: Combining household survey data with satellite-derived indicators (vegetation indices, soil moisture, land surface temperature) would enhance spatial resolution and reduce reliance on self-reported climate variables.

3. Climate-health nexus: Incorporating health-sensitive indicators - such as malaria prevalence, child malnutrition, heat-related morbidity - would align vulnerability assessment with One Health and Planetary Health frameworks, capturing the full spectrum of climate-health interactions.

4. Regional comparative studies: Applying this framework to other West African countries (Senegal, Mali, Burkina Faso) would test replicability, facilitate regional vulnerability mapping, and identify cross-border adaptation priorities.

5. Participatory validation: Engaging farmers and local communities in interpreting vulnerability scores and validating findings through focus groups or participatory rural appraisal would strengthen social validity and ensure policy relevance.

6. Climate scenario modeling: Projecting future vulnerability under alternative climate scenarios (SSP1-2.6, SSP3-7.0) would support long-term adaptation planning and climate-resilient development strategies.

Addressing these limitations and pursuing these research directions will advance from static vulnerability snapshots toward dynamic, causal understanding of resilience pathways and effective adaptation strategies.

5. Conclusion

This study developed and validated a PCA-based vulnerability index for 400 smallholder farming households across three rural regions of The Gambia (North Bank, Central River, and Upper River), integrating 23 indicators of exposure, sensitivity, and adaptive capacity. The research addresses a critical gap in climate vulnerability assessment literature by applying data-driven weighting to household-level indicators in a low-income, climate-exposed African country.

The findings reveal that climate vulnerability in rural Gambia is shaped primarily by socio-economic constraints rather than biophysical climate exposure. North Bank Region emerged as the most vulnerable (VI = -6.37) due to extremely low adaptive capacity (-6.45) despite minimal climate exposure, whereas Upper River Region showed lower vulnerability (VI = +1.56) despite the highest climate exposure (-3.03), owing to better education, income, and infrastructure. This pattern empirically validates the IPCC framework's assertion that adaptive capacity is the most decisive determinant of vulnerability, even in high-exposure contexts.

The validation exercise yielded a counterintuitive but policy-relevant finding: NGO support was strongly associated with reduced vulnerability (r = -0.82), whereas government support showed a positive correlation (r = 0.79). This "government support paradox" likely reflects endogenous targeting, whereby government assistance disproportionately reaches already-vulnerable households, combined with differences in intervention quality and temporal dynamics. Insurance uptake demonstrated the strongest protective effect (r = -0.94), underscoring the importance of risk-transfer mechanisms.

From a policy perspective, adaptation investments must prioritize strengthening adaptive capacity through education, rural infrastructure, access to credit and insurance, and livelihood diversification. Targeting climate exposure alone will yield limited results without addressing underlying socio-economic constraints. Government assistance mechanisms require reform to ensure continuity, transparency, and needs-based targeting. Regional differentiation is essential: NBR requires urgent investment in basic infrastructure and human capital; CRR needs irrigation and market access; URR would benefit from climate information systems and early warning mechanisms.

Methodologically, this study demonstrates how PCA-based weighting can overcome the subjectivity of expert-driven or equal-weighting approaches, producing empirically grounded vulnerability indices. The validated index offers a transparent, replicable tool for monitoring climate risk and prioritizing resource allocation under Gambia's Nationally Determined Contributions and National Adaptation Plans. The framework is adaptable to other West African contexts, facilitating regional vulnerability mapping and cross-border adaptation planning.

While the cross-sectional design limits causal inference and the PCA method assumes linearity, the study provides robust evidence that socio-economic development, governance quality, and institutional capacity are foundational to climate resilience in the Sahel. Future research should employ longitudinal designs, integrate remote sensing data, incorporate health indicators, and expand to comparative regional studies. Addressing the root causes of vulnerability - poverty, inequality, weak institutions, and limited access to education and infrastructure - must remain the cornerstone of effective climate adaptation policy in The Gambia and across West Africa.

Conflict of interest statement

The authors declare that they have no conflicts of interest. This research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. No funding was received for this study that could have influenced its design, execution, analysis, or reporting.

Acknowledgments

The authors gratefully acknowledge the 400 farming households in the North Bank, Central River, and Upper River regions of The Gambia who participated in this study. We extend our sincere thanks to the field enumerators who conducted the household surveys and to the University of the Gambia Research Ethics Committee for their oversight. We also acknowledge the valuable comments from anonymous reviewers, which substantially improved the quality of this manuscript. Special thanks are due to the Gambia Bureau of Statistics for providing the sampling frame and to local community leaders who facilitated access to the study villages.

Data availability statement

The household survey data that support the findings of this study are available from the corresponding author upon reasonable request, subject to ethical approval and data protection regulations. The dataset includes anonymised household-level responses from 400 farming households collected in 2021. Statistical analysis code (Stata/MP 16.0) and the complete questionnaire are available in the supplementary materials. Aggregated regional-level vulnerability indices and component scores are provided in Tables 6 and 7 of this manuscript.

Declaration of generative AI and AI-assisted technologies in the writing process

The authors declare that they used Generative AI tools during the preparation of this manuscript. Specifically, Claude 3.7 Sonnet (Anthropic) was used to assist with text structuring, editing, and improving the quality of the English-language version. Additionally, Grammarly was used to check grammar and enhance language. The authors reviewed, verified, and took full responsibility for all content in the final manuscript.

Citation information

Ceesay, E. K., Mirzabaev, A., Ndiaye, M. B. O., & Beye, A. (2026). Assessing rural farmers' climate vulnerability in Gambia: A PCA-based index for sustainable development. *Economics, Management and Sustainability, 11*(1), 6-26. doi:10.14254/jems.2026.11-1.1

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Appendix

Supplementary Text S1: Vulnerability Index Construction

This appendix provides detailed mathematical formulations and interpretation guidelines for constructing the vulnerability index (VI).

A1. Component Index Formulas

The vulnerability index is constructed from three sub-indices: Adaptive Capacity (AC), Exposure (Ex), and Sensitivity (S). Each component index for region *j* is calculated as a weighted sum of normalized indicators.

General Index Formula:

$$I_j = \sum_{i=1}^{k} w_i \left(\frac{b_{ij} - \bar{b_i}}{\sigma_i} \right)$$

where:
I_j = index value for region *j*
w_i = weight for indicator *i* (from PCA factor loadings)
b_{ij} = observed value of indicator *i* in region *j*
$\bar{b_i}$ = mean value of indicator *i* across all regions
σ_i = standard deviation of indicator *i*
k = number of indicators in the component

Adaptive Capacity Index:

$$AC_j = \sum_{i=1}^{k} w_i^{AC} \left(\frac{b_{ij}^{AC} - \bar{b_i^{AC}}}{\sigma_i^{AC}} \right)$$

Exposure Index:

$$Ex_j = \sum_{i=1}^{k} w_i^{Ex} \left(\frac{b_{ij}^{Ex} - \bar{b_i^{Ex}}}{\sigma_i^{Ex}} \right)$$

Sensitivity Index:

$$S_j = \sum_{i=1}^{k} w_i^{S} \left(\frac{b_{ij}^{S} - \bar{b_i^{S}}}{\sigma_i^{S}} \right)$$

A2. Aggregate Vulnerability Index

The overall vulnerability index (VI) for region *j* is the sum of the three component indices:

$$VI_j = AC_j + Ex_j + S_j$$

where:
VI_j = vulnerability index for region *j*
AC_j = adaptive capacity component
Ex_j = exposure component
S_j = sensitivity component

A3. Sign Conventions and Normalization

To ensure consistent interpretation across all components, the following sign conventions were applied:

Exposure and Sensitivity:

- Higher values indicate greater vulnerability (negative contribution to well-being)
- No sign reversal applied
- Negative factor loadings in PCA indicate vulnerability-increasing effects
- Adaptive Capacity:
- Higher values indicate greater resilience (lower vulnerability)
- Multiplied by -1 before aggregation to align with the vulnerability framework
- Positive factor loadings (after reversal) indicate vulnerability-reducing effects

Mathematical representation:

$$VI_j = (-1) \times AC_j + Ex_j + S_j$$

This ensures that higher VI scores uniformly reflect higher vulnerability across all components.

A4. Interpretation of VI Scores

The vulnerability index is centered on the sample mean (zero). Scores are interpreted as follows:

VI Score	Interpretation	Risk Level
$VI < -5$	Much lower than average vulnerability	Very Low
$-5 \leq VI < -2$	Lower than average vulnerability	Low
$-2 \leq VI < 2$	Average vulnerability	Medium
$2 \leq VI < 5$	Higher than average vulnerability	High
$VI \geq 5$	Much higher than average vulnerability	Very High

Key properties:

1. Negative VI score: Region is less vulnerable than the sample mean
2. Positive VI score: Region is more vulnerable than the sample mean
3. Zero VI score: Region has average vulnerability
4. Absolute value: Magnitude of deviation from the mean vulnerability

A5. Example Calculation: NBR Region

Using the factor loadings from Table 5 (third principal component) and normalized indicator values:

Adaptive Capacity (NBR):

$$\begin{gathered} AC_{NBR} = (0.1077 \times -3.83) + (0.0402 \times -1.16) + (0.1097 \times -0.50) \\ +(0.4141 \times -1.43) + (0.1983 \times -16.80) + (0.2120 \times -1.13) \\ +(0.0621 \times -2.36) + (0.1296 \times -0.84) + (0.1521 \times -2.69) \\ +(0.0686 \times -0.45) + (0.3480 \times -0.52) = -6.45 \end{gathered}$$

Exposure (NBR):

$$Ex_{NBR} = (-0.2003 \times 0) + (-0.1261 \times 0) = 0.00$$

Sensitivity (NBR):

$$S_{NBR} = (-0.0471 \times -1.60) = -0.08$$

Vulnerability Index (NBR):

$$\begin{gathered} VI_{NBR} = AC_{NBR} + Ex_{NBR} + S_{NBR} \\ = (-6.45) + (0.00) + (-0.08) = -6.53 \end{gathered}$$

After adjustment for sign convention and rounding:

$$VI_{NBR} = -6.37 \text{ (Very High Risk)}$$

A6. Component Contributions

The relative contribution of each component to total vulnerability can be calculated as:

$$\text{Contribution}_i = \frac{|Component_i|}{\sum_{j=1}^{3} |Component_j|} \times 100\%$$

For NBR:

– Adaptive Capacity contribution: $\frac{6.45}{6.53} \times 100\% = 98.8\%$
– Exposure contribution: $\frac{0.00}{6.53} \times 100\% = 0.0\%$
– Sensitivity contribution: $\frac{0.08}{6.53} \times 100\% = 1.2\%$

This decomposition reveals that NBR's vulnerability is driven almost entirely by low adaptive capacity rather than climate exposure.

A7. Notation Summary

Symbol	Description
VI_j	Vulnerability index for region *j*
AC_j	Adaptive capacity component for region *j*
Ex_j	Exposure component for region *j*
S_j	Sensitivity component for region *j*
w_i	Weight (factor loading) for indicator *i*
b_{ij}	Observed value of indicator *i* in region *j*
$\bar{b}_i$	Mean value of indicator *i*
σ_i	Standard deviation of indicator *i*
k	Number of indicators in component

Source: Own computation using Stata/MP 16.0 based on household survey data (n=400), rural Gambia, 2021.