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Livelihood vulnerability of food systems in Agro-Ecological Region I of Southern Zambia

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Climate change has significantly disrupted the food systems and livelihoods of low-resource rural communities, particularly in Southern Zambia's Agroecological Region I. Agroecological Region I, receives mean annual rainfall of less than 800 mm with an increasing reliance on rain-fed agriculture. This study evaluates the vulnerability of food system livelihoods to climate change in Kazungula, Gwembe, Chirundu, and Siavonga districts using the LVI-IPCC framework outlined in the sixth assessment report (IPCC-AR6) of the Intergovernmental Panel on Climate Change. The LVI-IPCC for the respondents was formed by combining its three components; exposure, sensitivity, and adaptive capacity from 195 rural households, who were selected using a stratified random sampling method. LVI was employed to identify the differential vulnerability of the four districts to climate change effects. An explanatory sequential mixed-methods design was employed, in which quantitative household survey data ($n = 195$) were first used to construct the Livelihood Vulnerability Index (LVI) and LVI-IPCC metrics, followed by focus group discussions and key-informant interviews to contextualise and interpret observed vulnerability patterns. Results show that households across all districts perceived climate change primarily through erratic rainfall, droughts, rising temperatures, and shifting rainfall seasonality, with perceived climate risk intensity varying significantly by district due to differences in livelihood sensitivity and adaptive capacity rather than hazard exposure. With regards to vulnerability, Siavonga had the highest vulnerability (LVI-IPCC $= 0.0711$) due to high exposure and limited adaptive capacity, while Kazungula had the lowest vulnerability (0.022). Dependence on rain-fed crop production was the main factor affecting sensitivity across districts. Farmers perceived rising temperatures, erratic rainfall, and reduced yields, confirming the consistency between the measured and perceived risks. These findings indicate that the impacts of climate on food systems stem from interconnected biophysical and socioeconomic pressures. It is crucial to strengthen the adaptive capacity of smallholder farmers in this region through irrigation interventions, livelihood diversification, and integrating early warning systems and climate-information services. The study provides evidence to guide district-level adaptation planning and facilitates the development of context-specific strategies that increase the resilience of food systems in Agroecological Region I and similar regions in Southern Zambia.

KEYWORDS

agroecological region I, climate change vulnerability, food systems resilience, livelihood vulnerability index, LVI-IPCC framework, smallholder, Zambia

1 Introduction

Climate variability continues to undermine food systems globally by disrupting production, markets, and consumption pathways (Schneider et al., 2023). Semi-arid regions are disproportionately affected because they are heavily dependent on climate-sensitive livelihoods. Limited adaptive capacity, poor infrastructure, and institutional weaknesses intensify these effects in Sub-Saharan Africa (Makondo and Thomas, 2024). Southern Zambia's Agroecological Region I (AER I) exemplifies such vulnerability. The region receives less than 800 mm of annual rainfall and experiences recurrent droughts, high evapotranspiration, and soil fertility decline. These climatic stresses directly threaten smallholders' livelihoods and local food security [Zambia Statistical Agency (ZSA), 2022]. Agroecological Region I has recently experienced increased climatic shocks (Makondo and Thomas, 2024; Chisengele and Nyanga, 2025a). Rain-fed agriculture, with maize, sorghum, and cowpeas as dominant crops, is the main source of livelihood. Limited irrigation, weak infrastructure, and poor access to climate-information intensify risk (Chisengele and Nyanga, 2025a). Most farmers rely on subsistence systems with low input use and limited diversification, increasing their exposure to rainfall fluctuations and market shocks (Makondo and Thomas, 2024). The interaction of climatic and socio-economic pressures defines the vulnerability of food systems in this region.

Southern Zambia's Agro-Ecological Region I faces chronic food insecurity, worsened by recurrent droughts and floods. In 2019/2020, 2.3 million rural people (25% of the rural population) were severely food insecure, with 16% in IPC Phase 3 (Crisis) and 3% in Phase 4 (Emergency), particularly in Gwembe, Chirundu, Siavonga, and Kazungula (Southern African Development Community, 2019). Vulnerability assessments show that 45 to 60% of rural households in Southern Province experience moderate to severe food insecurity, with Gwembe, Siavonga, and Chirundu consistently among the highest-risk districts due to drought-induced yield losses exceeding 40% and livestock mortality (Southern African Development Community, 2019; Government of the Republic of Zambia, 2023; African Risk Capacity, 2022). In 2023/2024, 2.04 million people (21% of the rural population) faced acute food insecurity (IPC Phase 3 or worse), including 58,440 in Phase 4, affecting 76 districts, many in Southern Province (Government of the Republic of Zambia, 2023). In Zambia, 76% of smallholder farmers remain vulnerable, with female-headed households most affected (Ngoma and Finn, 2024). This context of entrenched and severe food insecurity underscores the relevance of LVI-IPCC vulnerability analysis to disentangle exposure, sensitivity, and adaptive capacity, thereby clarifying the magnitude of results and guiding targeted resilience interventions such as irrigation and early warning systems (World Bank, 2018). Within this context vulnerability assessment frameworks offer a critical tool for disentangling the relative contributions of exposure, sensitivity, and adaptive capacity in shaping household and district-level resilience outcomes.

Globally, integrated frameworks linking exposure, sensitivity, and adaptive capacity are increasingly being used to examine food system vulnerability (Hahn et al., 2009; Saha et al., 2024). These frameworks explain how climate hazards influence household assets and institutional environments, shaping resilience outcomes (Mandal et al., 2025). For example, Zou and Yoshino (2017) applied spatial composite indices to identify hotspots of environmental vulnerability in China, demonstrating that physical and social variables jointly determine risk. In Bangladesh, Ali and Hossen (2022) found that reliance on a single livelihood source amplified household sensitivity to climatic stress. Similarly, Tofu et al. (2025) demonstrated that asset diversification and institutional support significantly reduce vulnerability in Ethiopia's arid zones.

The Livelihood Vulnerability Index (LVI) and LVI-IPCC have been applied to quantify the composite vulnerability levels in smallholder contexts across Asia (Phuong et al., 2023; Yu et al., 2024; Kumari et al., 2025). These studies reveal that socio-economic sensitivity drives vulnerability more than physical exposure. Similar findings have emerged from Ghana, Kenya, and Ethiopia, where the risk of climate vulnerability increases due to dependence on rain-fed crops, limited markets, and inadequate adaptive capacity (Omoyo et al., 2015; Baffoe and Matsuda, 2018; Zeleke et al., 2023). These studies emphasise the multidimensional nature of food system livelihood vulnerability and the need for integrated adaptation strategies.

In Zambia, growing research has explored how climate change interacts with livelihoods and ecosystems to produce vulnerability. Makondo and Thomas (2024) examined multidimensional poverty and ecosystem-based adaptation and concluded that vulnerability is perpetuated by structural inequality and weak institutional capacity. However, few studies have disaggregated these patterns by district or focused on Agroecological Region I, where climatic stress is most acute. Existing assessments remain largely descriptive and lack spatially differentiated evidence to guide adaptation planning (Farinós-Dasí et al., 2024). They also seldom integrate farmers' risk perceptions, which are essential for understanding behavioural responses and adopting climate innovations.

Chisengele and Nyanga's (2025a) recent synthesis work deepened this understanding by reviewing Southern Zambia's drivers of change, knowledge systems, and vulnerability patterns. Their analysis underscores that Region I experiences increased exposure to drought and extreme temperatures, but weak knowledge integration between scientific and indigenous systems undermines local resilience. They further argued that the resilience of the food system depends on bridging this divide through participatory learning and localised adaptation strategies. Despite these advances, empirical district-specific analyses, particularly those that link quantified vulnerability indices with farmers' climate perceptions, remain limited. Other regional studies have highlighted the importance of integrating quantitative assessments with risk perception. Rehman et al. (2023) and Saha et al. (2024) found that smallholders' climate change perceptions often mirror measured vulnerabilities, such as rising temperatures, erratic rainfall, and declining yields.

Abbreviations: LVI, Livelihoods Vulnerability Index; IPCC, Intergovernmental Panel on Climate Change; AER, Agro Ecological Region.

Farmers' climate change awareness shapes adaptive decisions and influences community resilience. Including perception data enhances the understanding of vulnerability and strengthens the policy relevance of index-based assessments. However, such integration is rarely implemented in the agroecological region I of Zambia, particularly in Southern Province, leaving a gap in localised evidence for resilience programming (Zeleke et al., 2023).

Climate change affects food systems through both direct and indirect pathways. The direct effects include declining yields and crop failures, whereas the indirect effects involve disruptions in markets, transport, and labour availability (Schneider et al., 2023). Drought episodes disrupt supply chains, reduce household incomes, and increase reliance on food assistance in Agroecological Region I in Southern Zambia Repeated exposure to such events reduces coping capacity, reinforcing poverty cycles. Livelihood diversification remains low, and access to credit or extension services is often constrained (Makondo and Thomas, 2024). Despite periodic humanitarian interventions, generations of vulnerability persist. Improved vulnerability assessments are essential for developing global adaptation policies. Recent advances employ spatial composite indices and multiple indicators to identify vulnerability hotspots (Zou and Yoshino, 2017; Srivastava et al., 2025). Mandal et al. (2025) demonstrated how resilience investment is informed by integrating climatic and socio-economic indicators. Applying similar tools in Agroecological Region I in Zambia can help policymakers efficiently allocate resources and design context-specific interventions. These include promoting small-scale irrigation, strengthening climate-information systems, and enhancing livelihood diversification to buffer against rainfall shocks (Saha et al., 2024; Srivastava et al., 2025).

Despite extensive global evidence, research on food system vulnerability in Southern Zambia remains inadequate. Few studies have generated district-level evidence linking exposure, sensitivity, and adaptive capacity across the Zambezi Valley. The limited integration of risk perception and food system perspectives has constrained the understanding of how climate impacts propagate through local economies (Ali and Hossen, 2022). Additionally, empirical data on AER I determinants of adaptive capacity, such as access to markets, institutions, and social capital, remain scarce (Makondo and Thomas, 2024). These knowledge gaps limit evidence-based planning for climate-resilient livelihoods.

Therefore, this study assesses the vulnerability of food system households to climate impacts in the Agroecological Region I of the Kazungula, Gwembe, Chirundu, and Siavonga districts of Southern Zambia. The LVI and LVI-IPCC frameworks are used to quantify vulnerability and identify key drivers. The research also analyses how farmers' perceptions correspond with measured vulnerability levels, providing a nuanced understanding of local risk realities. The findings contribute to the resilience agenda of Zambia by generating actionable insights for district-level adaptation planning. Ultimately, this study strengthens the empirical foundation for designing context-specific strategies that enhance smallholder resilience within Southern Zambia's semi-arid, rain-fed food systems.

This study makes three key contributions. Firstly, it provides district disaggregated assessment of food system livelihood vulnerability in Agro-Ecological Region I, an area that remains underrepresented in vulnerability research. Secondly, it applies the Livelihood Vulnerability Index (LVI) and the IPCC-aligned LVI-IPCC framework to explicitly link exposure, sensitivity and adaptive capacity of food system outcomes. Thirdly, it integrates farmers' perceptions of climate risk with index-based vulnerability metrics, thereby strengthening the interpretive and policy relevance of the analysis. Empirically, the study employs an explanatory sequential mixed methods research design, combining household survey data from 195 households with focus group discussions and key informant interviews. The quantitative analyses include index construction, comparative statistics, and regression modelling complemented by qualitative thematic analysis.

2 Methodology

2.1 Description of the study area

This study was conducted in Agroecological Region I of Southern Zambia, covering the districts of Kazungula, Gwembe, Siavonga, and Chirundu as shown in Figure 1. This region is located within the Zambezi Valley and is the country's driest zone. The average annual rainfall is less than 800 mm, and the average temperature is 21 °C. The area experiences high evapotranspiration rates and frequent dry spells, exposing households to food insecurity. Soils are largely sandy and low in fertility, limiting crop productivity without external inputs. Livelihoods in the region are diverse but heavily dependent on rain-fed agriculture. The main activities include crop and livestock production, fishing, and small-scale trading. The dominant crops are maize, sorghum, cowpeas, and groundnuts. The primary livestock assets are cattle, goats, and poultry. Fishing on Lake Kariba and the Zambezi River provides food and income sources. Seasonal trading of grain, charcoal, and fish also contributes to household earnings. However, recurrent droughts and unpredictable rainfall patterns increasingly threaten livelihoods, underscoring the importance of assessing vulnerability and adaptive capacity (Makondo and Thomas, 2024; Chisengele and Nyanga, 2025a).

2.2 Research design

An explanatory sequential mixed methods design was adopted to integrate quantitative and qualitative evidence. The design allowed for the quantification of household vulnerability using numerical indices, followed by qualitative explanations of observed patterns. First, quantitative data were collected through semi structured household surveys. This phase was followed by qualitative fieldwork using focus group discussions (FGDs) and key informant interviews (KIIs) to enrich interpretation. The design ensured triangulation and improved the validity of the findings through the convergence of data sources (Hahn et al., 2009; Saha et al., 2024).

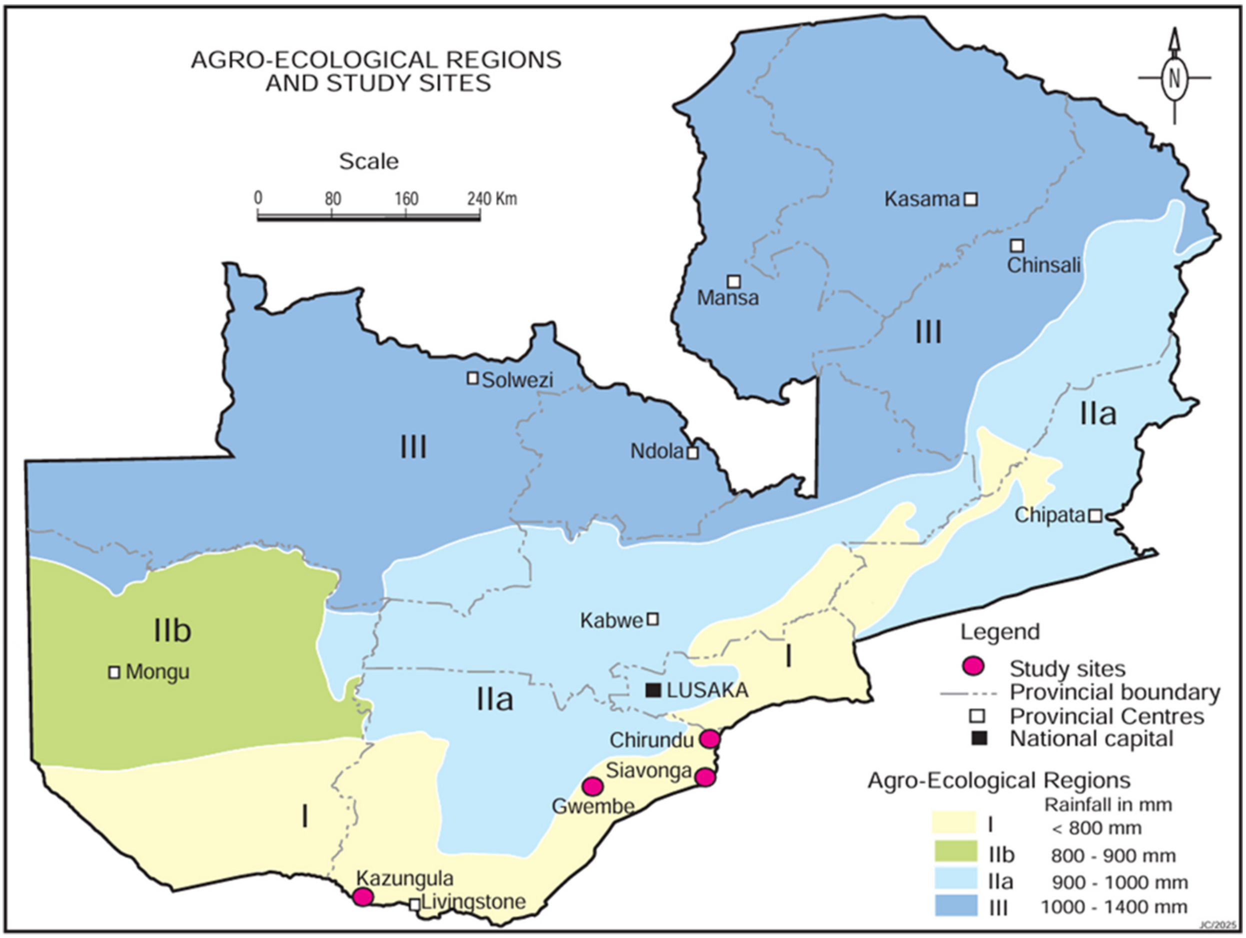

FIGURE 1
Map of study areas.

2.3 Sampling procedure and sample size determination

The study targeted rural households within the four districts engaged in agriculture production. The sample size was determined using *a priori* power analysis conducted in GPower software (Faul et al., 2007; Kang, 2021), assuming a medium effect size ($f = 0.25$), a 95% confidence level and statistical power of 0.8. The choice of a medium effect size conventional benchmarks for social and environmental research as cited by Chaokromthong and Sintao (2021) and is consistent with previous livelihood vulnerability studies conducted in farming contexts (Saha et al., 2024; Kumari et al., 2025; Mandal et al., 2025)

Although the power analysis indicated a minimum sample of 200 households, the sample size was increased to 204, distributed equally among the four districts, to account for potential non-response during fieldwork. However, only 195 complete and valid household observations (Kazungula-52; Siavonga-43; Gwembe-50 and Chirundu-50) were retained for the final analysis. A multistage stratified random sampling technique was used. The first stage involved purposive sampling of target districts representing Agroecological Region I in the Southern Province of Zambia. The second stage identified agricultural camps based on population density and livelihood diversity. Villages were randomly selected within each camp, followed by a random selection of households from village registers provided by local leaders. This approach minimised sampling bias and ensured spatial representation across the study zone.

Out of the 15 districts comprising the Southern Province, six fall within Agro-Ecological Region I. This study purposively focused on four of these districts namely Kazungula, Gwembe, Chirundu, and Siavonga as these represent predominantly rural, agriculture-dependent livelihoods within the Zambezi Valley and exhibit high exposure to recurrent droughts and rainfall variability (Makondo and Thomas, 2024). Livingstone was excluded due to its highly urbanised economy, while Sinazongwe was excluded due to overlapping livelihood characteristics with Gwembe. Within the selected districts, agricultural camps constituted the primary sampling strata. Kazungula District has 32 agricultural camps, of which approximately 20 fall within Agro-Ecological Region I. However, nearly half of these camps have undergone significant land-use change from agriculture to tourism and cross-border trade due to proximity to international borders with Zimbabwe, Namibia, and Botswana, resulting in reduced agricultural activity (Matanzima, 2024; da Corta and Bwalya, 2025). Siavonga and Chirundu districts each comprise 10 agricultural camps, while

TABLE 1 Summary of major components, sub-components, and associated vulnerability dimensions.

Major component	Sub- component	Typical indicators/ measures	IPCC vulnerability dimension
1. Socio-demographic profile	Household size; age dependency ratio; education level; female-headed households	Mean household size; percentage of dependents; years of education; % female-headed households	Adaptive capacity
2. Livelihood strategies	Livelihood diversification; land ownership; access to credit; livestock ownership	Number of livelihood sources; landholding size (ha); access to loans (%); tropical livestock Units	Adaptive capacity
3. Social networks	Membership in farmer groups; institutional linkages; remittances; participation in cooperatives	% households in groups; access to extension (%); % receiving remittances	Adaptive capacity
4. Health access	Access to medical facilities; disease prevalence; distance to health centre	% households within 5 km of facility; % reporting illness; Mean distance (km)	Sensitivity
5. Food security	Food sufficiency; market access; food diversity	Months of adequate food; Distance to market (km); dietary diversity score	Sensitivity
6. Water access	Water availability; source reliability; distance to source; months of water shortages	% households with reliable source; frequency of shortage; distance (km)	Sensitivity
7. Natural disasters and climate variability	Drought frequency; flood incidence; temperature and rainfall variability	Number of droughts in 10 years; rainfall CV %; mean temperature deviation (°C)	Exposure

Gwembe has 16 camps, of which two fall within Agro-Ecological Region II and were therefore excluded (Makondo and Thomas, 2024). The sampling frame was constructed using Ministry of Agriculture records of active farmers which is defined as households engaged in agricultural production for at least the past 5 years supplemented by village-level household registers obtained from local leaders.

Although the number of agricultural camps and active farming households varies across districts, equal household sample sizes were adopted to facilitate robust comparative analysis of livelihood vulnerability across districts (Awazi and Quandt, 2021). The objective of the study was not to estimate population-weighted prevalence but to examine relative vulnerability patterns across distinct food-system contexts. Findings are therefore interpreted comparatively rather than as population-level estimates.

2.4 Data collection methods

2.4.1 Quantitative data collection

Quantitative data werecollected using a pre-tested questionnaire administered between April 2025 and September 2025. The questionnaire captured information on seven major components consistent with the Livelihood Vulnerability Index (LVI) framework: (i) sociodemographic profile, (ii) livelihood strategies, (iii) health access, (iv) food security, (v) water access, (vi) social networks, and (vii) natural hazards and climate variability. Additional questions covered risk perception and adaptation behaviours of the smallholder farmers. Data were collected by trained enumerators fluent in English and local languages (Tonga, Lozi, and Nyanja). To ensure data accuracy, consistency, and ease of processing, the enumerators were trained on research ethics, interviewing techniques, and digital data entry procedures using ODK.

2.4.2 Qualitative data collection

Three Focus Group Discussions (FGDs) were conducted per district giving a total of 12 FGDs. Each district hosted one male-only, one female-only, and one mixed-gender group, with 12 participants per FGD, ensuring gender balance. Discussions explored perceptions of climate risks, coping strategies employed, livelihood changes, and adaptation barriers. Key informant interviews ($n = 16$) were conducted to capture institutional perspectives on climate resilience. These included two traditional leaders, one agricultural extension officer, one provincial climate expert from Ministry of Agriculture, one climate resilience project officer from NGOs, and two representatives from private seed companies in each district. Interviews explored institutional roles, adaptation interventions, and barriers to policy implementation.

2.5 Analytical framework: LVI and LVI-IPCC

This study applies the Livelihood Vulnerability Index (LVI) framework proposed by Hahn et al. (2009), subsequently aligned with the IPCC vulnerability framework to derive the LVI-IPCC. The LVI organises indicators into seven major components, which are regrouped under the IPCC vulnerability dimensions of exposure, sensitivity, and adaptive capacity (Table 1). Exposure indicators capture households' experience of climatic hazards and variability, including drought frequency, rainfall variability, and temperature anomalies. Sensitivity indicators reflect the degree to which food systems are affected by climate stresses, measured through access to water, food security outcomes, and health-related indicators. Adaptive capacity indicators represent households' ability to cope with and adjust to climate impacts and include socio-demographic characteristics, livelihood strategies, and social-network variables. Normalisation of Indicators:

All indicators were normalised using min–max scaling to ensure comparability across units and measurement scales. Subcomponents and major components were equally weighted following standard LVI applications to avoid subjective bias (Hahn et al., 2009; Phuong et al., 2023). The following quantitative indicators were standardised to a 0–1 scale using the min–max normalisation method:

$$Index_{S_d} \frac{S_{\max} - S_{\min}}{S_{\min} - S_{\max}} \tag{1}$$

where S_d represents the observed value of the district, and $S_{\max}$ and $S_{\min}$ are the maximum and minimum values across districts, respectively.

Subcomponent aggregation: each sub-component score was computed as the average of its standardised indicators.

Major component index: exposure, sensitivity, and adaptive capacity of the major components were obtained by averaging their respective sub-component scores.

2.5.1 LVI construction

Following standard livelihood vulnerability assessment procedures, household-level subcomponent scores were computed by aggregating standardised indicators using a weighted approach. To ensure internal consistency and comparability across households, the aggregation was implemented as a normalised weighted mean rather than an unscaled weighted sum.

LVI calculation: the Livelihood Vulnerability Index (LVI) was calculated as a weighted average of all major components:

$$S_i = ((\Sigma_k \, w_k \, x_{ik}))/(\Sigma_k w_k) \tag{2}$$

where S_i represents the subcomponent score for household i, $X_i k$ denotes the standardised value of indicator k for household i, and W_k is the assigned weight of indicator k. Normalising by the sum of the weights ensures that the resulting subcomponent scores are not mechanically influenced by the number or magnitude of indicators and remain directly comparable across households and districts. Where equal weighting was applied, Equation 2 simplifies to the arithmetic mean of the standardised indicators within each subcomponent.

LVI-IPCC framework: to align with the IPCC approach, the three components were aggregated to compute the LVI-IPCC:

$$LVI_i - IPCC_i = (Exposure_i - Adaptive\ Capacity_i) \times Sensitivity_i \tag{3}$$

Positive values indicate higher vulnerability, while negative values represent higher resilience.

2.6 Data analysis

The quantitative data were analysed using Minitab and R Studio (R 4.5.1). Minitab was used for preliminary descriptive and inferential statistical tests, including ANOVA and *post-hoc* comparisons, while R Studio (version 4.5.1) was used for index construction, regression analysis, correlation analysis and, graphical visualisation given its flexibility for reproducible statistical workflows (Thulin, 2024). Descriptive statistics summarised the socio-economic characteristics and indicator distributions. Inferential analysis, including ANOVA and Tukey *post-hoc* tests, assessed statistical differences in LVI and LVI-IPCC values across districts and gender categories. Correlation analyses were conducted to examine the relationships between vulnerability components and selected sociodemographic variables. To examine factors associated with households' perception that climate change is occurring, a multivariable logistic regression model was estimated (Equation 4a). The dependent variable was binary, taking a value of 1 if the respondent perceived that climate change is occurring and 0 otherwise. Explanatory variables included household socio-demographic characteristics, livelihood attributes, and district fixed effects. The model is specified as follows:

$$\begin{aligned} Logit\,[P\,(Y_i = 1)] \;=\; & \beta_0 + \;\beta_1 \log\,(1 + Income_i) + \beta_2 HHsize_i \\ & + \;\beta_3 Age_i + \beta_4 Gender_i + \beta_5 Education_i \\ & + \;\beta_6 Land_i + \beta_7 District_i + \;\varepsilon_i \end{aligned} \tag{4}$$

where Y_i denotes household's perception of climate change, β_0 is the intercept, β_k are estimated coefficients, and ε_i is the error term. Odds ratios are reported to facilitate interpretation of effect sizes.

To assess determinants of perceived climate risk intensity, an ordinary least squares (OLS) regression model was estimated using the composite likelihood–severity risk score as a continuous dependent variable (Equation 4b). The model included perceived climate hazard exposure, household socio-economic characteristics, and district fixed effects. The model is specified as:

$$\begin{aligned} Risk_i \;=\; & \beta_0 + \beta_1 HazardIndex_i + \beta_2 \log\,(1 + Income_i) + \beta_3 HHsize_i \\ & + \;\beta_4 Age_i + \beta_5 Gender_i + \beta_6 Education_i \\ & + \;\beta_7 Land_i + \beta_8 District_i + \;\varepsilon_i \end{aligned} \tag{5}$$

where $Risk_i$ represents the perceived climate risk intensity for $HHsize_i$ represents household size, $HazardIndex_i$ captures perceived exposure to multiple climate hazards, and the remaining terms are defined as above. Model diagnostics were conducted to assess multicollinearity and heteroskedasticity.

Qualitative data from FGDs and KIIs were analysed thematically using NVivo. The transcripts were coded inductively to identify patterns related to climate perception, adaptation strategies, and institutional roles. Themes were triangulated with quantitative findings to explain district variations and contextualise vulnerability determinants. The results were integrated during interpretation, consistent with the sequential explanatory design.

2.7 Ethical considerations

Before data collection, all participants were informed about the study's objectives, confidentiality, and voluntary participation. Written informed consent was obtained from all participants. Ethical approval was granted by the University of Zambia Natural and Applied Sciences Research Ethics Committee (NASREC: 2025-APR-007). Before the fieldwork, permission was also sought from the District Agricultural Coordinating Offices (from the Ministry of Agriculture) and traditional leaders. Data were anonymized and securely stored to protect the respondents' privacy.

3 Results

3.1 Socio-demographic characteristics of respondents

Educational attainment was generally low across the study area. Most respondents had attained primary education, while secondary education was less common and tertiary education was rare (Figure 2). District-level differences in educational profiles were modest, with no district exhibiting markedly higher levels of post-primary education.

Household demographic characteristics displayed moderate variability. Age distributions of respondents were broadly comparable across districts, with similar median ages and overlapping interquartile ranges (Figure 3). Household size showed greater dispersion, with larger household sizes observed in Gwembe and Siavonga compared to Chirundu and Kazungula (Figure 3). Income distributions were highly skewed across all districts, with low median monthly incomes and substantial within-district variability, particularly in Kazungula and Gwembe (Figure 3).

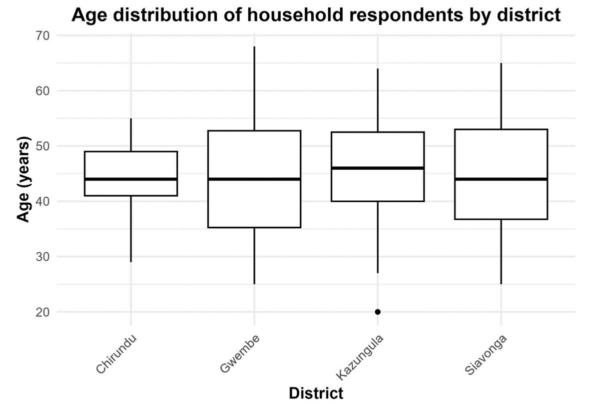

FIGURE 2
Age distribution of household respondents by district.

A total of 195 households were surveyed across the four study districts (Figure 1), with relatively balanced representation: Kazungula ($n = 52$), Gwembe ($n = 50$), Chirundu ($n = 50$), and Siavonga ($n = 43$). The results indicate that most respondents (70%) were aged between 15 to 35 years, showing a predominantly youthful farming population (Figure 2). Male-headed households ($\approx$ 58%) were slightly more represented than female-headed ones (Figure 3; Table 2A). Education levels were generally low with about 72 of the respondents reporting having attained primary education, while less than 5% reached tertiary level (Figure 4; Tables 2B, C). In terms of household monthly incomes, the majority of respondents ($\approx$60%) earned below ZMW 1,000 per month as shown in Figure 5. Average household size clustered around four to six members (Figure 6).

3.2 Household perceptions of climate risks and hazards

Perceptions of climate-related hazards were widespread across the study area (Figure 7; Tables 3, 4). Decreasing rainfall was the most prevalent reported by 99.5% of the respondents followed by extended periods of severe droughts (96.9%), erratic rainfall patterns (88.7%), extended periods of drought, increasing temperatures, and delayed onset or early cessation of the rainy season (Table 4). Severe windstorms (54.4%), and wildfires were perceived less uniformly but were still reported by about 17.4%

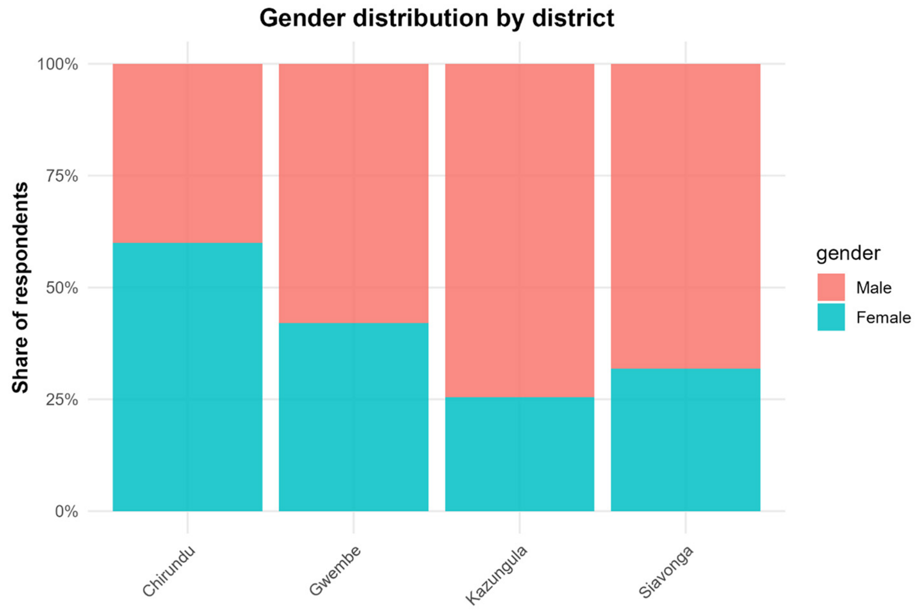

FIGURE 3
Gender distribution of respondents by district.

of the respondents. District-level analysis revealed broadly similar perception patterns, although the intensity and consistency of reported hazards varied (Figure 8). Gwembe and Chirundu exhibited higher proportions of households reporting droughts and rainfall variability, while Kazungula and Siavonga showed relatively higher reporting of flood events and temperature extremes (Table 5). Gender-disaggregated analysis indicated only modest differences in hazard perceptions between male and female respondents (Figure 9; Table 5). In most districts, both genders reported similar exposure to major climate hazards, suggesting that climate risks are widely experienced at the household level rather than differentiated primarily by gender.

TABLE 2 Variables used in the regression analysis.

2A: Gender characteristics		
Category	***n***	**%**
Male	118	60.5
Female	77	39.5
Total	**195**	**100.0**
2B: Education level		
Education level	***n***	**%**
No formal education	6	3.1
Primary education	145	74.4
Secondary education	41	21.0
Tertiary education	3	1.5
Total	**195**	**100.0**
2C: District descriptive statistics		
District	***n***	**%**
Kazungula	52	26.7
Chirundu	50	25.6
Gwembe	50	25.6
Siavonga	43	22.1
Total	**195**	**100.0**

3.3 Perceived climate hazard exposure index

To synthesise household-level perceptions of multiple hazards, a perceived climate hazard exposure index was constructed. The distribution of the index indicates moderate variability across households, with most observations clustering around the mean and relatively few extreme values (Figure 10; Table 5). Mean exposure scores were broadly comparable across districts, with Gwembe recording the highest mean exposure, followed closely by Chirundu and Kazungula, while Siavonga exhibited slightly lower average exposure (Table 5). However, analysis of variance indicated that differences in mean exposure across districts were not statistically significant ($p < 0.005$), suggesting that perceived climate hazard exposure is relatively uniform across Agro-Ecological Region I.

3.4 Determinants of climate change perception

A logistic regression model was used to examine household-level determinants of perceiving climate change. The dependent variable captured whether respondents reported that the climate is changing. Results indicate that household socioeconomic and demographic characteristics had limited explanatory power

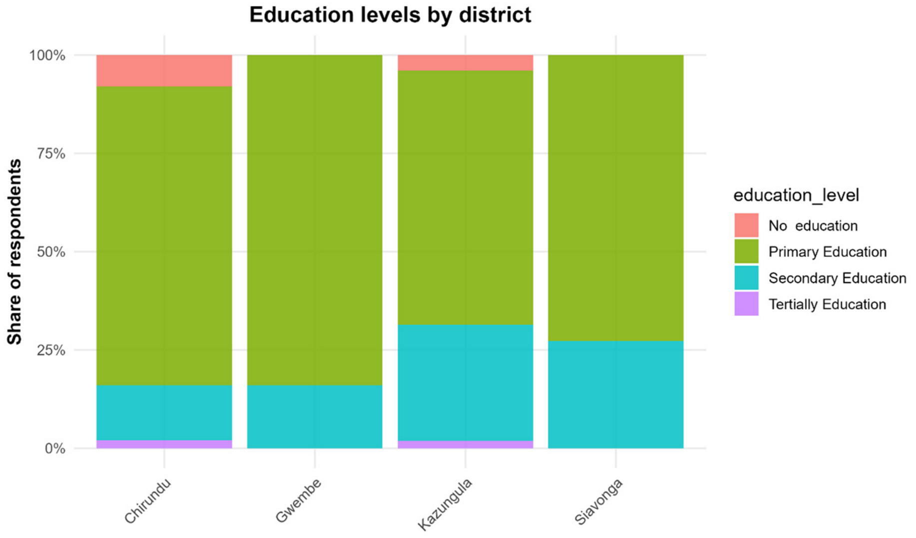

FIGURE 4
Education level by district.

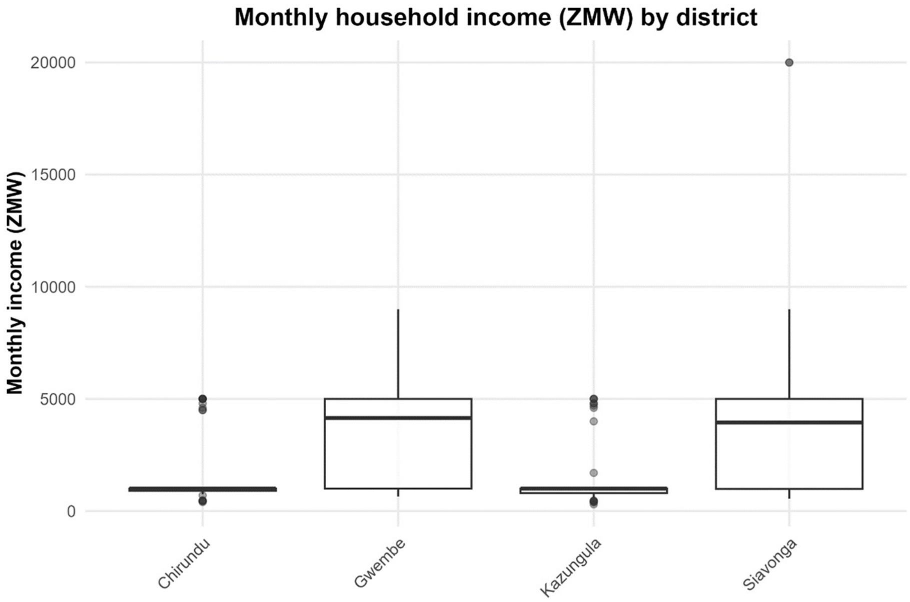

FIGURE 5
Monthly income by district.

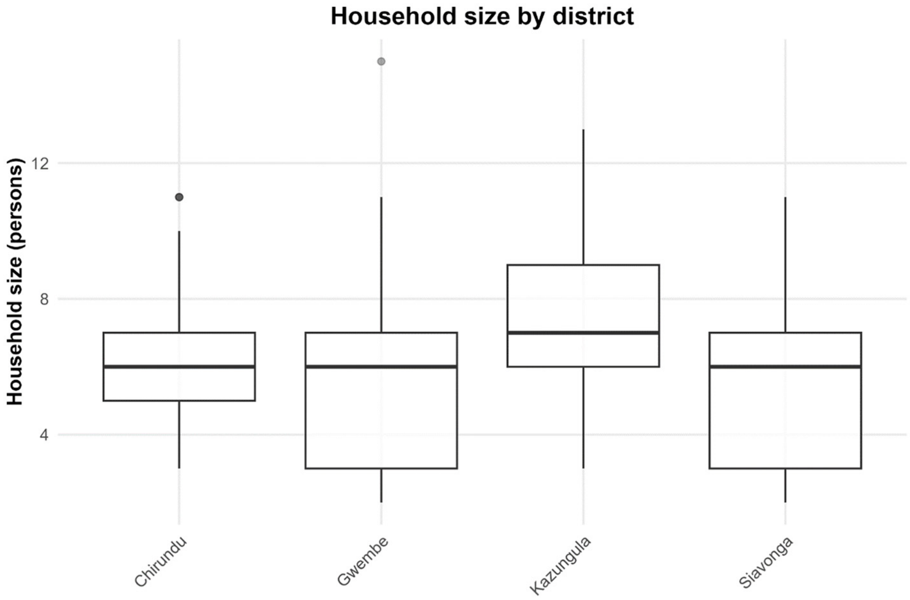

FIGURE 6
Household size by district.

(Table 6). Household income, household size, age, gender, education level, and farmland size were not statistically significant predictors of climate change perception. District effects were more pronounced, with households in Gwembe showing higher odds of perceiving climate change compared to the reference district, although this effect was marginally significant ($p < 0.093$).

Overall model fit was modest, as reflected by Tjur's R^2 (0.057), indicating that perception of climate change is widespread and only weakly differentiated by observed household characteristics (Table 7).

3.5 Livelihood Vulnerability Index (LVI) across districts

Table 8 presents the Livelihood Vulnerability Index (LVI) values disaggregated by district and major components. The LVI scores range from 0.409 to 0.704 across the seven dimensions, indicating moderate to high livelihood vulnerability among smallholder households in Southern Zambia's Agroecological Region I. Siavonga (LVI = 0.535) and Gwembe (LVI = 0.531) recorded the highest overall vulnerability scores, suggesting that

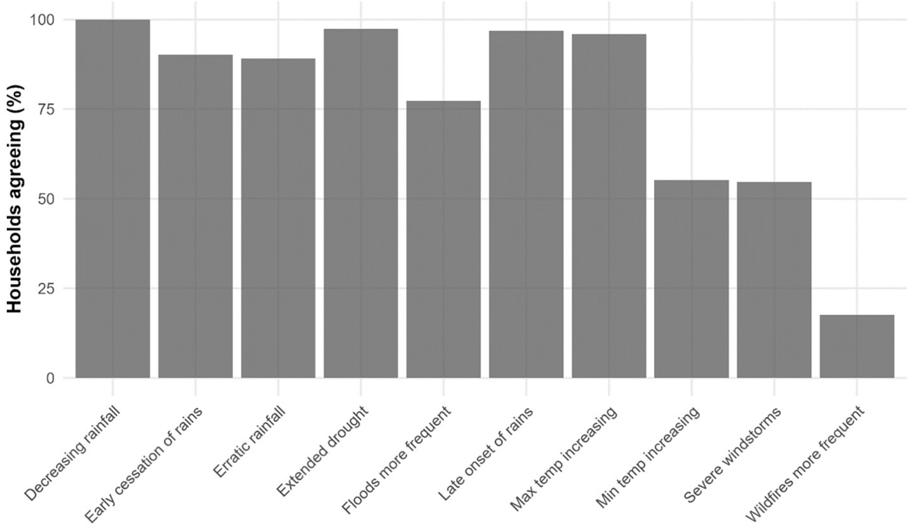

FIGURE 7
Household perceptions of climate hazards.

TABLE 3 Descriptive statistics of household characteristics and food system vulnerability indices (*n* = 195).

Variable	*n*	Mean	SD	Median	Min	Max	Skewness	Kurtosis
Age (years)	195	44.66	9.39	44	20	68	−0.00	−0.46
Monthly income (ZMW)	195	2,523.44	2,740.24	1,000	300	20,000	2.97	14.81
Household size	195	6.25	2.48	6	2	15	0.58	0.22
Adult household members	195	2.07	0.37	2	1	4	1.39	6.30
Farmland size (ha)	195	7.50	3.19	8	3	15	0.44	−0.74
Exposure index (E)	195	0.59	0.17	0.59	0.18	0.91	−0.19	−0.92
Sensitivity index (S)	195	0.51	0.08	0.51	0.19	0.70	−0.37	0.99
Adaptive capacity index (AC)	195	0.50	0.11	0.49	0.20	0.83	0.14	−0.19
LVI–IPCC	195	0.05	0.10	0.05	−0.26	0.28	0.00	−0.41

households in these districts face relatively greater livelihood stress. Chirundu (LVI = 0.509) showed intermediate vulnerability, while Kazungula (LVI = 0.496) was the least vulnerable, though still within the moderate range. The most sensitive dimensions across all districts were livelihood strategies, water access, and natural disasters and climate variability. Livelihood strategies recorded consistently high scores of between 0.626 to 0.655, reflecting over-dependence on rain-fed agriculture and limited diversification into off-farm income. Water access (0.473–0.602) was a major stressor, especially in Kazungula, where recurrent droughts and shallow wells constrain year-round availability. Natural disasters and climate variability were critical in Siavonga (0.704) and Gwembe (0.695), confirming recurrent drought exposure and erratic rainfall patterns. By contrast, health and social networks registered relatively lower vulnerability scores (0.387–0.518), suggesting moderate access to basic services and community support. The socio-demographic profile and food security components displayed minimal district variation, implying structural vulnerability shared across the study area. Overall, the composite LVI results highlight that Siavonga and Gwembe are the most vulnerable districts, while Kazungula is the least.

3.6 Livelihood Vulnerability Index

3.6.1 Visual comparison of livelihood vulnerability components

Figure 11 illustrates the Livelihood Vulnerability Index (LVI) component profiles across the four study districts. The radar plot clearly shows distinct differences among vulnerability dimensions. Siavonga and Gwembe exhibit the widest polygons, indicating higher overall vulnerability relative to Kazungula and Chirundu. The spikes under natural disasters and climate variability confirm that these two districts face frequent droughts and rainfall variability. Elevated scores for livelihood strategies and water access reflect over-reliance on rain-fed farming and limited off-farm diversification options. In contrast, Kazungula displays narrower arms in most dimensions, suggesting relatively stronger adaptive mechanisms through better water access and market connectivity. Chirundu lies between the two extremes, showing moderate vulnerability in most categories but reduced social-network support. The convergence of lines across the health and food-security components demonstrates shared systemic constraints in basic service delivery and nutrition across Agroecological Region I. Collectively, the spider diagram confirms that Siavonga and Gwembe are the most climate-sensitive and least diversified districts.

TABLE 4 Household perceptions of climate hazards in Agro-Ecological Region I of Southern Zambia.

Climate hazard	% Agree
Extended periods of severe drought	**96.9**
Decreasing amount of rainfall	**99.5**
Late onset of the rainy season	**96.4**
Early cessation of the rainy season	**89.7**
Increasing maximum temperatures	**95.4**
Increasing minimum temperatures	**55.1**
Flood events more frequent	**76.9**
Erratic rainfall more frequent	**88.7**
Severe windstorms	**54.4**
Frequent experience of wildfires	**17.4**

This table shows that nearly all households perceived rainfall-related hazards and drought, whereas hazards such as wildfires and windstorms were reported less frequently. The values represent the percentage of households agreeing that the hazard has increased or become more frequent.

3.7 Spider diagram—LVI indicators

3.7.1 Livelihood Vulnerability Index (LVI)-IPCC

The livelihood Vulnerability Index-IPCC (LVI-IPCC) was calculated by regrouping the seven primary indicators into three IPCC-defined components namely, Adaptive Capacity, Sensitivity, and exposure.

3.7.2 LVI–IPCC framework analysis across districts

Table 9 and Figure 12 presents the Livelihood Vulnerability Index–IPCC (LVI–IPCC) results showing composite scores for exposure, sensitivity, and adaptive capacity across the four districts of Agroecological Region I. The results demonstrate inter-district variability in household vulnerability, reflecting diverse ecological and socio-economic conditions.

TABLE 5 Mean perceived climate hazard exposure and risk intensity by district.

District	Hazard exposure index (mean ± SD)	Climate risk intensity (mean ± SD)
Chirundu	0.834 ± 0.126	19.02 ± 3.15
Gwembe	**0.844 ± 0.119**	**22.56 ± 3.14**
Kazungula	0.812 ± 0.124	**13.40 ± 2.93**
Siavonga	0.801 ± 0.155	**23.39 ± 3.02**

This table indicates that Gwembe and Siavonga recorded the highest mean climate risk intensity, while Kazungula exhibited substantially lower perceived risk.

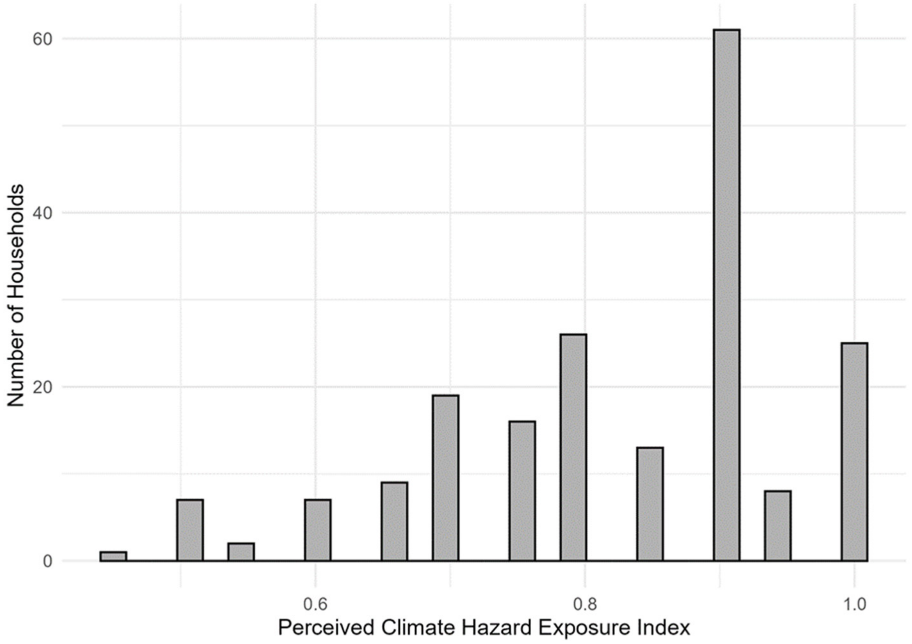

FIGURE 8
Perceived climate hazard exposure index.

3.8 LVI-IPCC among districts

The results show Significant differences in LVI-IPCC among districts ($p = 0.042$) with Siavonga and Kazungula having the most significant while others were not statistically significantly different (p=0.042). This means intra-district variability is crucial in assessment of livelihood vulnerability.

3.9 Gender-based analysis of LVI-IPCC components

The results showed that the females had high Sensitivity compared to the males ($p = 0.042$). But no significant differences in overall LVI-IPCC scores on exposure and adaptive capacity ($p = 0.0001$). Implying that both males and females have the same exposure and limited adaptive capacity. Furthermore, no significant gender differences in Social networks, food security, Health access, Water access and livelihood strategies between males and females. This means that structural vulnerability dominates over geographic/income effects. Females face higher sensitivity and socio-demographic vulnerabilities (socio-demographics: female = 0.572 vs. male = 0.346; $p < 0.0001$).

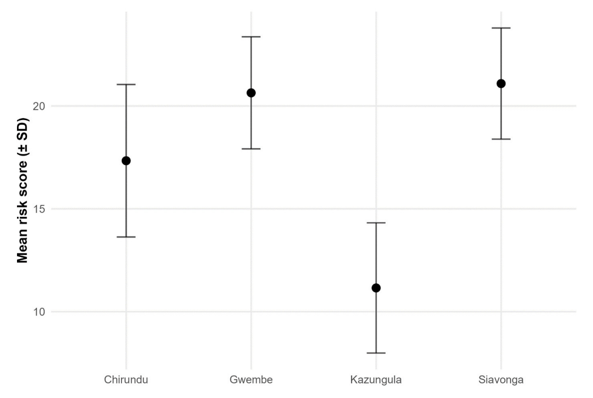

FIGURE 9
Households perceptions of climate hazards by district and gender.

3.10 Regression analyses—LVI-IPCC

Regression analysis to test whether LVI-IPCC can be predicted by socioeconomic factors such as household income, age, and household size showed that income and age were not good predictors ($p = 0.805$ and $p = 0.651$ respectively) while household size had significant effects ($p = 0.048$). These results imply that Household size negatively predicts vulnerability while Income and age are not predictive.

3.11 Validation of the LVI-IPCC vulnerability model

To assess the explanatory validity and policy relevance of the LVI-IPCC framework, predicted livelihood vulnerability (mean LVI-IPCC at village level) was compared with observed food security outcomes (mean meals per day and mean months of food shortage), aggregated from 195 households across 33 villages. Village-level scatterplots (patterns consistent with district aggregates) indicated a moderate negative association between mean LVI-IPCC and mean meals per day, with higher predicted

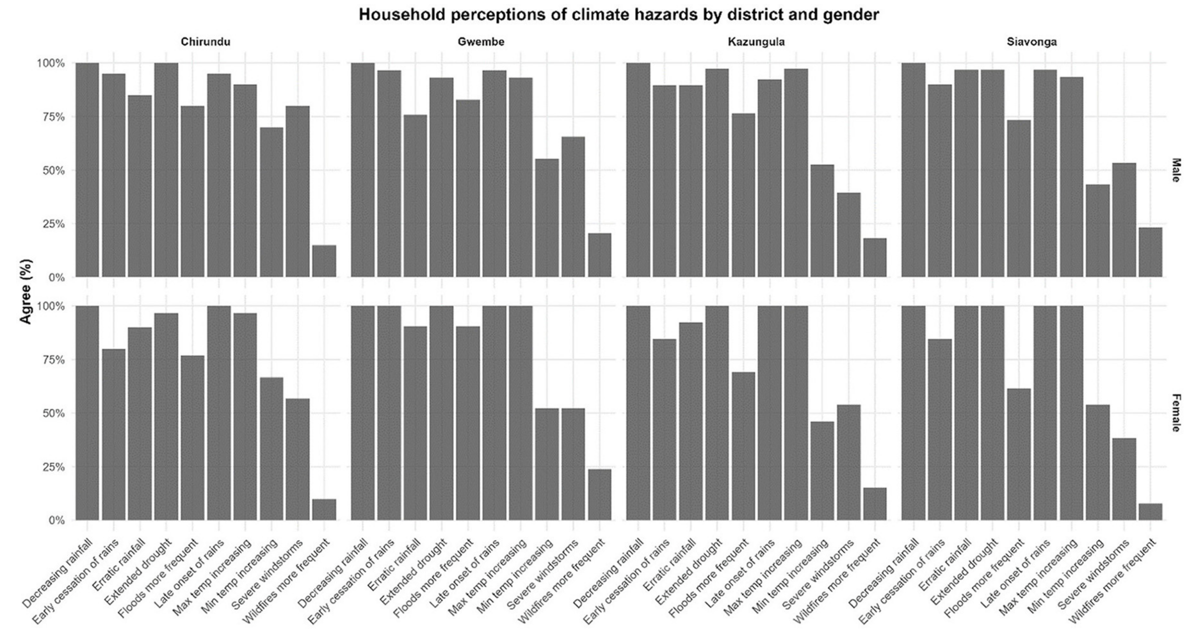

FIGURE 10
Perceived climate risk intensity by district.

TABLE 6 Logistic regression results for factors associated with the perception that the climate is changing.

Variable	Odds ratio (OR)	95% CI	p-value
Log household income	0.69	0.40–1.08	0.134
Household size	1.16	0.96–1.44	0.146
Age	1.00	0.95–1.05	0.965
Female (ref: male)	1.81	0.79–4.02	0.151
No education (ref: primary)	0.53	0.09–4.21	0.488
Secondary+ education	1.55	0.59–3.90	0.355
Farmland size (ha)	1.12	0.93–1.38	0.238
Gwembe (ref: Chirundu)	2.50	0.92–8.09	0.093
Kazungula (ref: Chirundu)	0.91	0.21–3.79	0.897
Siavonga (ref: Chirundu)	1.23	0.36–4.75	0.750

Odds ratios reported with 95% confidence intervals. Model fit: Tjur's $R^2 = 0.057$.

TABLE 7 Ordinary least squares regression results for perceived climate risk intensity.

Variable	Coefficient	Robust SE	p-value
Perceived climate hazard exposure index	−0.22	0.24	0.364
Log household income	−0.31	0.31	0.321
Household size	−0.01	0.12	0.913
Age	0.03	0.03	0.325
Female (ref: male)	−0.07	0.51	0.885
No education (ref: primary)	−0.15	1.35	0.912
Secondary + education	−0.14	0.58	0.809
Farmland size (ha)	−0.13	0.11	0.247
Gwembe (ref: Chirundu)	3.54	0.67	<0.001
Kazungula (ref: Chirundu)	−5.62	0.87	<0.001
Siavonga (ref: Chirundu)	4.37	0.79	<0.001

Robust standard errors (HC3) reported. Adjusted $R^2 = 0.61$; $N = 194$.

vulnerability linked to fewer meals per day (Figures 13, 14). The association with mean months of food shortage was weakly positive, with greater variability in high-vulnerability contexts (Figures 15, 16).

Dichotomising villages by vulnerability class (median split on mean LVI-IPCC) revealed that high-vulnerability villages had lower mean meals per day and slightly longer food shortage periods than low-vulnerability villages (Figures 13–16). Differences were not statistically significant ($p > 0.05$), attributable to intra-district heterogeneity and sample characteristics.

District-level comparisons provided clearer spatial insights (Table 10). Chirundu exhibited the highest mean LVI-IPCC (0.172 ± 0.011 SD; six villages) and lowest mean meals per day (2.112 ± 0.312 SD), with moderate shortage duration (5.011 ± 0.900 SD). Gwembe exhibited intermediate vulnerability (0.077 ± 0.014 SD; nine villages) but comparable food security challenges (meals/day: 2.139 ± 0.220 SD; shortage: 4.970 ± 0.770 SD). Kazungula had low vulnerability (0.010 ± 0.020 SD; 10 villages) and the highest meals per day (2.288 ± 0.347 SD), with shorter shortages (4.848 ± 0.890 SD). Siavonga displayed the lowest mean LVI-IPCC (−0.093 ± 0.037 SD; eight villages) and moderate food security (meals/day 2.154 ± 0.234 SD; shortage 4.809 ± 0.308 SD; Tables 10, 11).

These patterns offer partial empirical validation of the LVI-IPCC model, particularly the directional link between higher vulnerability and reduced food access (meals per day) in rain-fed systems (Tables 11–13). The village sample ($n = 33$) increases confidence in the index's ability to identify relative hotspots, although non-significant associations highlight limitations arising from heterogeneity and self-reported data.

4 Discussion

4.1 Overview of key findings

The results presented in Figure 1 and Table 3 show clear spatial differentiation in livelihood vulnerability across the four study districts of Southern Zambia's Agro-Ecological Region I. Siavonga and Chirundu recorded the highest LVI-IPCC composite values (0.0711 and 0.0556 respectively), while Kazungula had the lowest (0.0222), followed by Gwembe (0.0440). This pattern highlights that vulnerability is primarily a function of exposure to recurrent climatic hazards rather than socio-economic capacity differences. The radar diagram in Figure 2 reinforces this conclusion, showing that exposure values consistently exceed both sensitivity and adaptive capacity across all districts. Siavonga, with the highest exposure (0.6296) and one of the lowest adaptive-capacity scores (0.4911), emerges as the most vulnerable district. In contrast, Kazungula demonstrates the reverse trend: low exposure (0.5469) and relatively higher adaptive capacity (0.5014), resulting in a smaller LVI-IPCC differential. These findings confirm that exposure dominates the vulnerability structure in Region I, while adaptive capacity remains uniformly weak across the four districts. Gender-disaggregated analysis (not shown in the figure) revealed minimal statistical difference in total LVI-IPCC values, but female-headed households exhibited higher sensitivity due to limited access to productive assets, information, and institutional support. Education was found to correlate positively with adaptive capacity, echoing the centrality of human capital in resilience theory (Makondo and Thomas, 2024). The pattern of district-level variation thus points to structural rather than purely climatic determinants of vulnerability.

4.2 Climate risk perceptions of food systems among smallholder farmers

Across Kazungula, Gwembe, Chirundu, and Siavonga, household perceptions of climate change converge around lived experiences of erratic rainfall, prolonged droughts, rising temperatures, and shifts in rainfall seasonality. This alignment between perceived and observed climatic trends reflects patterns reported elsewhere in Zambia and across Sub-Saharan Africa,

TABLE 8 Livelihood Vulnerability Index (LVI) by district and major components in Agroecological Region I of Southern Zambia.

District	Socio-demographic profile	Livelihood strategies	Health	Social networks	Food security	Water access	Natural disasters and climate variability	Overall LVI
Kazungula	0.409	0.655	0.445	0.430	0.505	0.602	0.429	0.496
Gwembe	0.436	0.626	0.518	0.451	0.499	0.495	0.695	0.531
Chirundu	0.490	0.652	0.492	0.387	0.511	0.473	0.558	0.509
Siavonga	0.404	0.633	0.496	0.462	0.495	0.551	0.704	0.535

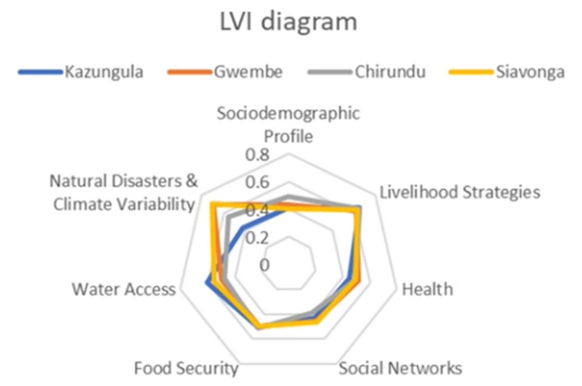

FIGURE 11
Radar (spider) diagram of Livelihood Vulnerability Index (LVI) components by district in Agroecological Region I of Southern Zambia.

TABLE 9 Livelihood vulnerability index–IPCC (LVI–IPCC) scores for exposure, sensitivity, adaptive capacity, and overall vulnerability across districts in Agroecological Region I of Southern Zambia.

District	LVI-IPCC across districts			
	Exposure	Sensitivity	Adaptive capacity	LVI-IPCC
Chirundu	0.6184	0.5092	0.5092	0.0556
Gwembe	0.5782	0.5212	0.4938	0.044
Kazungula	0.5469	0.4837	0.5014	0.022
Siavonga	0.6296	0.5133	0.4911	0.0711

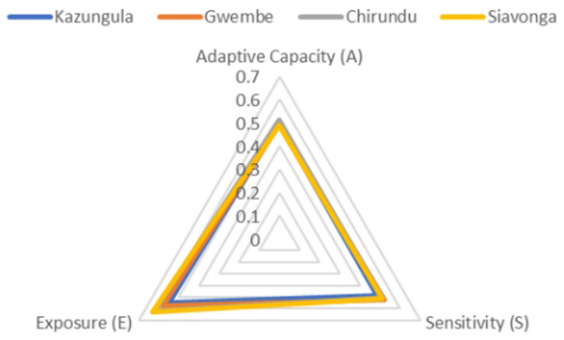

FIGURE 12
Vulnerability triangle diagram of LVI-IPCC contributing factors.

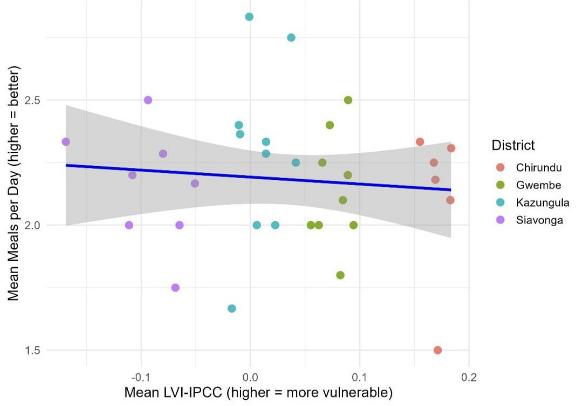

FIGURE 13
Relationship between Mean LVI-IPCC and Mean Meals per Day across districts.

where climate change is increasingly understood as an immediate and persistent livelihood stressor rather than a distant or abstract risk (Mubiru et al., 2015; Mulenga et al., 2017; Tesfahun and Chawla, 2020;). Such experiential framing underscores the salience of climate variability within rain-fed and semi-arid food systems. Despite this convergence, district-level differences reveal how local food system configurations shape dominant risk narratives. In Gwembe and Chirundu, perceptions are strongly drought-centred, reflecting chronic water scarcity and heavy dependence on rain-fed agriculture, consistent with findings from semi-arid systems in Ethiopia, Ghana, and Zimbabwe (Asravor, 2018; Tesfahun and Chawla, 2020; Mugari et al., 2023). In contrast, Kazungula and Siavonga households report more diversified climate risks, including floods and temperature extremes, shaped by proximity to major water bodies and low-lying landscapes, mirroring patterns observed in Tanzania and The Gambia (Below et al., 2015; Lambarraa-Lehnhardt et al., 2024). The limited gender differentiation observed suggests that climate risks are primarily experienced at the household level, supporting behavioural models that frame risk perception as context-specific and livelihood-embedded rather than demographically determined (Eitzinger et al., 2018; Azadi et al., 2019).

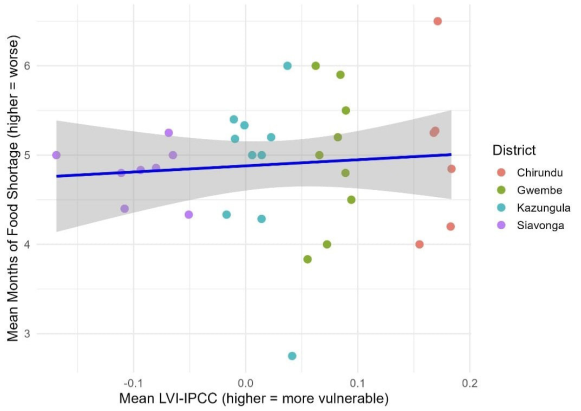

FIGURE 14
Relationship between Mean LVI-IPCC and Mean Months of food shortages across districts.

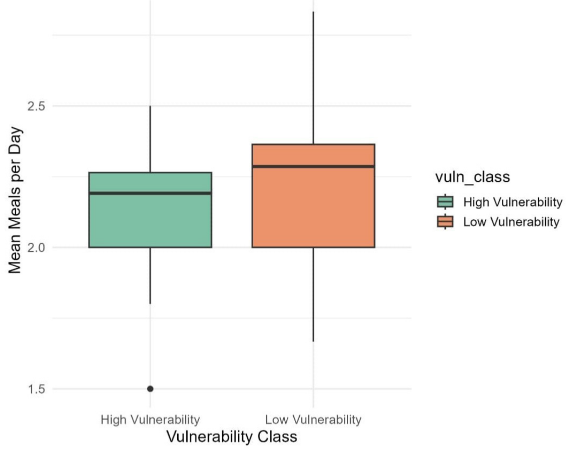

FIGURE 15
Mean meals per day by Vulnerability class.

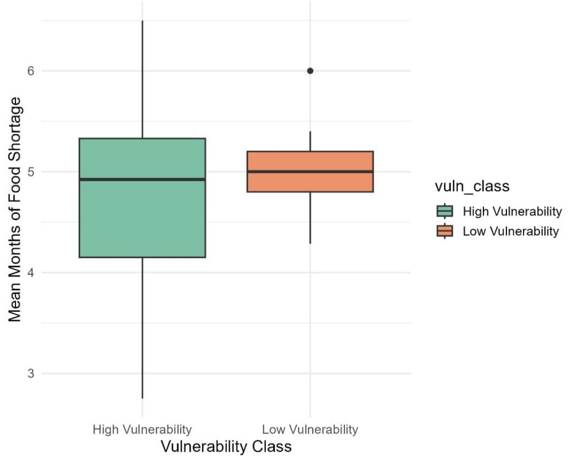

FIGURE 16
Mean months of food shortage by vulnerability class.

4.3 Perceived hazard exposure vs. climate risk intensity

Although climate hazards are widely perceived across all districts, the limited variation in perceived hazard exposure highlights a critical distinction emphasised in climate risk literature: exposure alone does not explain vulnerability or perceived risk intensity. Instead, risk emerges through the interaction of exposure with livelihood sensitivity and adaptive capacity, a pattern consistently reported in smallholder systems across Africa and other climate-stressed regions (Eitzinger et al., 2018; Mamun et al., 2021). The uniformity of exposure therefore provides a useful baseline against which differentiated vulnerability pathways can be interpreted. Regression analysis reinforces this distinction by showing that household-level socioeconomic characteristics do not significantly predict perceived climate risk intensity, while district-level effects dominate. Higher risk intensity in Gwembe and Siavonga reflects the compounding effects of water scarcity, livelihood specialisation, and limited diversification, which amplify the consequences of climate shocks even under comparable exposure conditions. Similar amplification mechanisms have been documented in semi-arid Ethiopia, Zimbabwe, and lake-adjacent systems in West and East Africa (Tesfahun and Chawla, 2020; Mamun et al., 2021; Mugari et al., 2023). Conversely, lower perceived risk in Kazungula suggests that market integration, livelihood diversification, and cross-border trade can moderate climate risk perception, consistent with recent evidence from Zambia and comparable contexts (Mulungu et al., 2024). These findings reinforce the need for place-based vulnerability assessments that prioritise food system structure and adaptive capacity over exposure metrics alone.

4.4 Livelihood vulnerability components

The multi-component LVI radar plot (Figure 3) reveals that livelihood strategies, water access, and natural hazards/climate variability were the most influential vulnerability drivers. Siavonga and Chirundu show pronounced spikes under these dimensions, confirming their sensitivity to recurrent droughts and limited diversification options. Kazungula's more balanced shape across components reflects its relatively diversified livelihood base and cross-border trade opportunities.

4.4.1 Sociodemographic profiles

The socio-demographic profiles depict low education levels, large dependency ratios, and limited income diversity across all districts factors that constrain adaptive capacity. This pattern mirrors findings from Ethiopia and Zambia, where human-capital deficits amplify vulnerability (Zeleke et al., 2023; Makondo and Thomas, 2024). Studies in Ghana and Nepal (Baffoe and Matsuda, 2018; Poudel et al., 2020) similarly link education to improved innovation adoption and climate-risk management. Unlike contexts such as Vietnam or India, where gendered

TABLE 10 Summary of village-level livelihood vulnerability indicators by district (aggregated data).

District	Number of villages	Total households	Mean LVI	Mean meals per day	Mean months of food shortage
Chirundu	6	49	0.172	2.11	5.01
Gwembe	9	50	0.077	2.14	4.97
Kazungula	10	52	0.010	2.29	4.85
Siavonga	8	43	−0.093	2.15	4.81
Overall	**33**	**194**	**0.042**	**2.19**	**4.92**

The Livelihood Vulnerability Index Values have been rounded to three decimal places for LVI and two for others. Overall means are unweighted (simple average across districts).

TABLE 11 Classification of villages by vulnerability, food insecurity, and meals per day ($n = 33$ villages).

District	High vulnerability	Low vulnerability	High insecurity	Low insecurity	High meals/day	Low meals/day	Total villages
Chirundu	6 (100%)	0 (0%)	3 (50%)	3 (50%)	3 (50%)	3 (50%)	6
Gwembe	9 (100%)	0 (0%)	4 (44%)	5 (56%)	4 (44%)	5 (56%)	9
Kazungula	1 (10%)	9 (90%)	5 (50%)	5 (50%)	7 (70%)	3 (30%)	10
Siavonga	0 (0%)	8 (100%)	1 (13%)	7 (87%)	4 (50%)	4 (50%)	8
Total	**16 (48%)**	**17 (52%)**	**13 (39%)**	**20 (61%)**	**18 (55%)**	**15 (45%)**	**33**

Percentages are row percentages (within district). Classifications are based on thresholds applied to mean LVI, mean months of food shortage, and mean meals per day.

education gaps are wide (Phuong et al., 2023; Kumari et al., 2025), Region I exhibits modest differences, suggesting that systemic economic barriers rather than educational inequality drive sensitivity. Strengthening adult and youth climate literacy programs, therefore, could yield significant adaptive dividends.

4.4.2 Livelihood strategies

All districts exhibit narrow livelihood portfolios dominated by rain-fed maize production, confirming over-reliance on a climate-sensitive system. This aligns with findings from the Ganges Delta and Bangladesh, where mono-cropping heightens vulnerability (Saha et al., 2024; Kayal and Chowdhury, 2025). The slight advantage of Kazungula stems from non-farm income and livestock sales, which reduce direct dependence on rainfall. The discordant evidence from parts of China and India (Kuang et al., 2020; Kumari et al., 2025), where diversification has reduced risk exposure, underscores how market isolation and financial exclusion perpetuate fragility in Zambia. Policies encouraging drought-tolerant crops such as millet and sorghum, alongside small-livestock and value-addition enterprises, are thus central to transforming vulnerability into resilience.

4.4.3 Water access

Water access was the most critical constraint, with pronounced seasonal shortages in Siavonga and Kazungula despite proximity to water bodies. As indicated in Figure 3, water access scores show strong divergence across districts. This finding resonates with hydrological vulnerability studies in Bangladesh and India (Ali and Hossen, 2022; Srivastava et al., 2025). The discordant evidence from irrigated settings such as Gujarat, where institutional water management mitigates exposure (Kumari et al., 2025), suggests that Region I's vulnerability stems not from scarcity *per se* but from poor storage, governance, and distribution. Expanding solar-powered irrigation and community-managed boreholes could substantially improve adaptive capacity and mitigate drought impacts.

TABLE 12 Cross-tabulation of vulnerability class vs. food insecurity class.

Vulnerability class	High insecurity	Low insecurity	Total
High vulnerability	7	9	16
Low vulnerability	6	11	17
Total	**13**	**20**	**33**

This table shows the overlap between livelihood vulnerability and food insecurity classifications across all villages in the study districts.

4.4.4 Health access

Health access contributed moderately to overall vulnerability, as seen from the relatively smaller segment on the radar plot (Figure 3). Distance to clinics and seasonal disease prevalence remain barriers, though less acute than in high-density contexts like Bangladesh (Azam et al., 2021). Improved rural health posts likely explain Zambia's lower health-vulnerability index relative to Iranian and South-Asian cases (Keshavarz et al., 2017). Nonetheless, health shocks indirectly reduce adaptive labour capacity; hence integrated public-health and agricultural advisory services could strengthen resilience outcomes.

TABLE 13 Selected high-vulnerability villages with largest sample sizes.

Camp name	District	Mean LVI	Mean meals/ day	Mean months shortage	Households	Vulnerability class	Insecurity class	Meals class
Kapululira	Chirundu	0.184	2.31	4.85	13	High	Low	High meals/day
Jamba	Chirundu	0.183	2.10	4.20	10	High	Low	Low meals/day
Lusitu	Chirundu	0.169	2.18	5.27	11	High	High	Low meals/day
Munyumbwe	Gwembe	0.085	2.10	5.90	10	High	High	Low meals/day

Selected villages have ≥10 households and/or particularly high LVI values and gives a good picture of priority areas for interventions.

4.4.5 Food security

Food security closely tracks climatic exposure. Districts with frequent droughts, notably Siavonga and Gwembe, report the shortest periods of adequate food supply, confirming the exposure–food security linkage observed in Kenya and Ethiopia (Omoyo et al., 2015; Zeleke et al., 2023). The superior performance of millet and cowpea over maize supports diversification into heat-tolerant crops. Similar transitions in India's arid zones and the Sahel have proven effective in stabilising household nutrition (Mandal et al., 2025; Tofu et al., 2025). Hence, promoting alternative grains and community storage systems could strengthen food resilience in Region I.

4.4.6 Natural hazards and climate variability

The "Natural Disasters and Climate Variability" axis dominates the LVI diagram, reflecting recurrent droughts and temperature extremes. Siavonga's high exposure aligns with World Meteorological Organisation (WMO) (2024) and Southern African Development Community (2019) reports on the 2023/24 El Niño drought. Similar exposure gradients have been recorded in China and the Himalayas (Zou and Yoshino, 2017; Zhu et al., 2025). The implication is clear: adaptation in Region I must shift from reactive assistance to anticipatory risk management, integrating early warning systems and index-based insurance mechanisms.

4.5 LVI–IPCC dimensions

Across all districts, exposure values exceed sensitivity and adaptive capacity, confirming that vulnerability is hazard driven. The dominance of exposure parallels evidence from India and Ethiopia (Zeleke et al., 2023; Kumari et al., 2025). Sensitivity is accentuated among female-headed households due to asset and service deficits, a pattern documented in Uganda and Bangladesh (Ali and Hossen, 2022; Nkurunziza et al., 2025). Adaptive capacity, although relatively stable across districts, remains low indicating systemic underinvestment in information, finance, and human capital. Increasing access to localised climate services, digital advisories, and social network strengthening would therefore directly improve adaptive capacity and resilience trajectories. Overall, Siavonga (0.0711) and Chirundu (0.056) recorded the highest LVI–IPCC values, indicating that households in these districts are the most vulnerable to climatic impacts. Gwembe (0.044) exhibited moderate vulnerability, while Kazungula (0.022) had the lowest value, suggesting relatively greater resilience. The high vulnerability of Siavonga arises from its elevated exposure score (0.6296) and limited adaptive capacity (0.4911). This district experiences frequent droughts, prolonged dry spells, and degraded soils, which intensify sensitivity to rainfall variability. Similarly, Chirundu shows high exposure (0.6184) and moderate sensitivity (0.5092), consistent with its semi-arid topography and dependence on rain-fed crops. Gwembe's vulnerability (LVI–IPCC = 0.044) is mainly linked to sensitivity (0.5212), reflecting limited diversification and food insecurity among smallholder households. Kazungula, in contrast, combines relatively low exposure (0.5469) with a slightly stronger adaptive capacity (0.5014), resulting in lower overall vulnerability. This aligns with its comparative access to markets, cross-border trade, and better water infrastructure. The LVI–IPCC results confirm that exposure is the dominant driver of vulnerability across the study districts, while adaptive capacity remains insufficient to offset climatic risks. The small differences in sensitivity (0.4837–0.5212) suggest that structural livelihood characteristics are similar across the region. These findings corroborate patterns observed by Makondo and Thomas (2024) and Chisengele and Nyanga (2025a), who reported that exposure to recurrent droughts and inadequate adaptation planning perpetuate vulnerability among Zambian smallholders. The observed hierarchy Siavonga > Chirundu > Gwembe > Kazungula reflects a spatial gradient of vulnerability shaped by both biophysical exposure and socio-economic resilience gaps.

Validation of the LVI-IPCC model indicates a directional association between higher predicted vulnerability and poorer food security outcomes, particularly reduced meals per day, in high-vulnerability districts such as Chirundu, whereas Kazungula exhibits lower vulnerability and better access. This aligns with evidence that droughts, the dominant shock in Zambia (Chisengele and Nyanga, 2025a), disproportionately affect rain-fed smallholders, with ∼76% nationally vulnerable and Southern Province hardest hit (Ngoma and Finn, 2023). The village sample ($n = 33$) strengthens confidence in the index's ability to identify hotspots, although modest statistical significance reflects intra-district heterogeneity and limitations in self-reported data. Adaptive capacity constraints in rain-fed systems amplify these linkages, underscoring the need for targeted interventions such as irrigation, diversification, and climate information services in high-exposure areas (Chisengele and Nyanga, 2025b; Ngoma and Finn, 2023; School Meals Coalition, 2025). Future validations could incorporate longitudinal or objective yield data to enhance predictive power amid escalating climate risks in Southern Zambia.

4.6 Spatial differentiation and synthesis

The composite vulnerability hierarchy (Siavonga > Chirundu > Gwembe > Kazungula) reflects the spatial pattern visualised in the radar charts, where Siavonga exhibits the widest exposure–capacity gap. The marginal yet significant difference between Siavonga and Kazungula in Table 1 suggests localised hotspots masked within aggregated means. These echoes spatial gradients in Ethiopia's drylands and the Indo-Gangetic plains (Venus et al., 2022). Kazungula's relative resilience can be attributed to trade connectivity and water investment evidence that economic diversification reduces climatic sensitivity. Thus, adaptive programming should follow a differentiated strategy: Siavonga and Chirundu prioritised for drought-insurance and irrigation infrastructure; Gwembe targeted for livelihood diversification; and Kazungula supported to consolidate and replicate its adaptive practices.

4.7 Implications and research directions

The results demonstrate that resilience in Southern Zambia hinges on multi-scalar interventions. Policies should prioritise hotspot targeting through early-warning systems, anticipatory financing, and gender-responsive planning. Investments in solar irrigation, rainwater harvesting, and catchment restoration will provide the greatest adaptive returns. Promoting climate-smart crop portfolios and expanding education and digital climate services through cooperative structures can elevate household adaptive capacity. Further research should pursue longitudinal LVI-IPCC assessments to capture seasonal variability and integrate satellite-derived drought indices with household data. Applying entropy weighting and machine-learning models could refine vulnerability diagnostics and identify nonlinear relationships among exposure, sensitivity, and adaptive capacity (Arora et al., 2025).

4.8 Advancing understanding

This study contributes a district-disaggregated assessment linking empirical vulnerability indices with farmers' perceptions in Zambia's driest agro-ecological zone. The integration of Figures 1, 2 provides a holistic visualisation of how exposure, sensitivity, and adaptive capacity interact to shape vulnerability. It demonstrates that exposure dominates, sensitivity is gendered and structural, and adaptive capacity remains shallow yet improvable. The framework developed here offers a replicable diagnostic for policymakers to translate vulnerability metrics into action—anchored on three interlocking pillars: water security, livelihood diversification, and social inclusion. Strengthening these pillars will be pivotal to advancing climate-resilient food systems in Southern Zambia and similar semi-arid regions of sub-Saharan Africa.

5 Conclusion and recommendations

This study provides district-level evidence on the livelihood vulnerability of food systems in Agro-Ecological Region I of Southern Zambia, demonstrating that exposure to recurrent climatic hazards particularly droughts and rainfall variability remains the dominant driver of vulnerability. While sensitivity and adaptive capacity vary modestly across districts, adaptive capacity remains uniformly low, underscoring systemic constraints related to water access, livelihood diversification, and institutional support. Siavonga and Chirundu emerge as the most vulnerable districts, while Kazungula exhibits relatively greater resilience linked to market access and water infrastructure. These findings have direct implications for climate adaptation and food-system planning in Southern Zambia. District and provincial authorities, in collaboration with the Ministry of Agriculture and the Disaster Management and Mitigation Unit, could prioritise targeted investments in water security, including small-scale irrigation and rainwater-harvesting infrastructure to reduce rainfall dependency and enhance year-round food production in the most vulnerable districts. Extension services and development partners may support livelihood diversification through the promotion of drought-tolerant crops such as cowpeas, sorghum, millet etc, small livestock, and value-addition activities to buffer climate shocks. Strengthening access to climate-information services and cooperative-based learning platforms, particularly for women and youth, would further enhance adaptive capacity. By aligning vulnerability diagnostics with institutional mandates, the LVI-IPCC framework applied in this study offers a practical tool for informing localised, evidence-based adaptation strategies in semi-arid food systems.

The evidence confirms that vulnerability is both climatic and systemic, rooted in socio-economic fragility, inadequate infrastructure, and weak institutional support. Enhancing adaptive capacity through education, water security, and livelihood diversification is therefore essential for transforming vulnerability into resilience. The application of the LVI–IPCC framework provides a replicable tool for policymakers and practitioners aiming to design targeted, evidence-based interventions in semi-arid, rain-fed food systems.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Ethics statement

The studies involving humans were approved by the Research Ethics Committee of the University of Zambia and the Ministry of Agriculture. Before the fieldwork, permission was also sought from the District Agricultural Coordinating Offices and traditional leaders. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

LC: Formal analysis, Visualization, Data curation, Conceptualization, Resources, Validation, Project administration, Software, Writing – review & editing, Methodology, Funding acquisition, Writing – original draft, Investigation. PN: Validation, Supervision, Methodology, Visualization, Funding acquisition, Writing – review & editing.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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