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Climate vulnerability at the household level: A behaviorally informed index and its application to refugees in Jordan

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Abstract
Climate vulnerability assessments have traditionally relied on macro-level indices and physical exposure models, overlooking household-level heterogeneity and the behavioral determinants of vulnerability. To fill this gap, we develop a general, replicable Climate Vulnerability Index (CVI) that measures climate vulnerability at the household level by integrating experience-based exposure, sensitivity, and behavioral adaptive capacity, including risk preferences, time preferences, climate knowledge, and observed adaptive behaviors, into the established IPCC vulnerability framework. The index classifies households into Low, Stress, Crisis, and Emergency categories of climate vulnerability based on a transparent hierarchical logic. Second, we apply this framework to the 2024 UNHCR Vulnerability Assessment Framework (VAF) in Jordan, a representative survey of the UNHCR-registered refugee population (N = 5,164 refugee households), producing the first behaviorally informed climate vulnerability profile of a national refugee population. Approximately 40 percent of households fall into concerning vulnerability categories and roughly 10 percent are classified as Emergency, with camp-based refugees systematically more vulnerable than those in host communities. Two validation exercises comparing self-reported exposure with objective climatic indicators and benchmarking the CVI against an independent national vulnerability mapping reveal that the household-level index captures dimensions of lived climate risk invisible to aggregate assessments. These findings underscore the value of integrating micro-level and behavioral dimensions into climate vulnerability measurement to improve targeting, anticipatory action, and resilience programming for displaced populations.

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1 Introduction

Climate change is increasing the frequency, intensity, and spatial reach of climatic hazards, placing mounting pressure on populations already living in precarious social, economic, and environmental conditions (Birkmann et al., 2022; Li et al., 2023; Patz et al., 2014). Displaced populations, and refugees in particular, face disproportionately high climate risk (Fransen et al., 2024). They often reside in substandard housing, have limited access to information, safe infrastructure and basic services, face mobility restrictions, and experience significant income and credit constraints (Carlson et al., 2017; Lalude, 2025; Ronzani, 2025). These conditions heighten both exposure to climatic hazards and sensitivity to their impacts, while simultaneously limiting the capacity to adapt (Stojetz et al., 2024a; Stojetz et al., 2024b). Yet, despite increasing recognition of the intersection between climate vulnerability and displacement (Ashour et al., 2023; Bera & Singh, 2021; Castro et al., 2025) there remains limited evidence on climate vulnerability at the household level, especially among refugee populations.

Existing climate vulnerability assessments tend to rely on macro-level indices, hazard exposure models, or asset-based proxies, often calibrated at district, national, or global scales (Al Qudah et al., 2021; Edmonds et al., 2020; Goujon et al., 2024; Pandey & Jha, 2012). While these tools provide valuable information for large-scale planning (Kala et al., 2023), they typically overlook the heterogeneity present within vulnerable populations and may fail to capture the granular, micro-level dynamics that shape vulnerability in low-income or displaced households (Baliki et al., 2022; Pandey & Jha, 2012). This limitation is particularly consequential in contexts where climate resilience interventions require fine-grained targeting to effectively reach those most at risk. In particular, standard vulnerability indices seldom include behavioral determinants of adaptive capacity—factors such as risk aversion, time discounting, climate knowledge, the uptake of adaptive behaviors, or attitudes toward long-term planning. Yet, these elements are critically important for understanding climate vulnerability as they influence how individuals interpret, prioritize, and respond to climatic risks.

Behavioral factors shape adaptation in several ways. First, they influence decision-making under uncertainty, including whether households invest in protective behaviors, diversify income sources, or adopt mitigation strategies. Second, they reflect cognitive load, stress, and constraints associated with displacement, all of which may diminish future-oriented thinking or risk preparedness. Third, behavioral indicators can reveal latent dimensions of vulnerability not observable in standard socio-economic metrics. Despite their importance, behavioral determinants are rarely included in vulnerability assessments due to data limitations.

Humanitarian surveys typically focus on immediate needs, shelter conditions, and asset ownership, with limited capacity to collect behavioral data.

This paper makes two contributions. First, we develop a household-level Climate Vulnerability Index (CVI) that integrates behavioral adaptive capacity into the established exposure–sensitivity–adaptive capacity framework (IPCC, 2022; Otto et al., 2017). The resulting measurement framework is designed to be replicable across displacement contexts wherever household survey data on climate exposure, sensitivity and adaptive capacity are available. By incorporating micro-level and behavioral dimensions that standard indices omit, the CVI offers a more comprehensive understanding of vulnerability and enables proactive targeting of climate adaptation resources.

Second, we apply this framework to the 2024 UNHCR Vulnerability Assessment Framework (VAF) in Jordan (UNHCR, 2024a; UNHCR, 2024b), producing the first behaviorally informed climate vulnerability profile of a national refugee population. The VAF is a nationally representative survey of refugees registered with UNHCR and, for the first time in 2023, includes a climate module. We document the distribution of vulnerability across refugee households, comparing outcomes between those living in the camps of Azraq and Zaatari and those residing in host communities. These comparisons reveal substantial heterogeneity and highlight the compounded disadvantage of camp residents. Within this application, we conduct two validation exercises. We critically compare the CVI's self-reported exposure component with independent climatic indicators, finding that household reports reflect cumulative climate burden rather than deviation-based shocks. We also compare the household-level CVI with an independently produced national-scale vulnerability mapping by the World Food Programme (WFP) and the Arab Water Council (AWC), showing that the two instruments capture complementary dimensions of climate risk. Understanding these divergences is important for improving coordination between humanitarian actors and national climate adaptation planners.

Jordan is a particularly suitable setting for this application. As one of the largest refugee-hosting countries globally, Jordan must manage both climate stress and humanitarian pressures in parallel. Refugees in Jordan face increasing heat stress, water scarcity, and flash-flood events, alongside challenges such as limited legal work opportunities, high debt burdens, and overcrowded housing (Binder et al., 2022; Al Mahasneh et al., 2023). These overlapping constraints create a complex risk landscape (Simpson et al., 2021) that is insufficiently captured by conventional vulnerability metrics. A household-level index integrating behavioral factors can offer more precise identification of households at greatest risk, improving the targeting of anticipatory cash programs, shelter upgrades, water-related interventions, and climate-resilient livelihoods.

The integration of behavioral data into vulnerability assessment offers methodological innovations relevant beyond Jordan. Many global indices assume that households with similar assets or demographics have similar adaptive capacity, yet evidence from behavioral economics shows that decision-making under scarcity varies widely (De Bruijn & Antonides, 2022; Ronzani et al., 2018; Burlacu et al., 2022), especially in contexts of conflict, weather shocks and forced displacement (Fransen et al., 2024; Ronzani et al., 2025; Stojetz et al., 2025). Incorporating behavioral adaptive capacity therefore enhances the diagnostic value of vulnerability assessments and may improve the allocation of climate adaptation resources.

The remainder of the paper is organized as follows. Section 2 presents the CVI as a general measurement framework, detailing its conceptual foundations, index architecture, and classification logic. Section 3 describes the empirical application, including the Jordanian context, the VAF data, and the operationalization of the index. Section 4 reports results on the distribution of vulnerability, camp–host community differences, and the two validation exercises. Section 5 discusses implications and limitations, and Section 6 concludes.

2 A Household-Level Climate Vulnerability Framework

2.1 Conceptual foundations

The CVI builds on the vulnerability framework articulated in successive IPCC assessments (IPCC, 2022), which conceptualizes vulnerability as a function of three components: exposure, sensitivity, and adaptive capacity. This tripartite structure is well established and has been operationalized in a large body of work, including national-level composite indices (Chen et al., 2023; Edmonds et al., 2020), district-level livelihood vulnerability indices (Hahn et al., 2009; Pandey & Jha, 2012), regional social vulnerability assessments (Vincent, 2004; Otto et al., 2017), and gridded hazard models (Al Qudah et al., 2021). These macro-level tools serve important planning functions (Kala et al., 2023), but they mask within-community heterogeneity in exposure, sensitivity and adaptive capacity and are limited in their applicability to displaced populations, in particular.

Exposure. Existing approaches typically capture exposure through biophysical hazard indicators measured at coarse spatial resolution—gridded temperature or precipitation data, satellite-derived hazard layers, or administrative-level event records. These measures assume that all households within a given grid cell or district face broadly similar exposure to climatic conditions and challenges. Yet, within small geographic areas, households' exposure to climate shocks and how they experience it can vary significantly (Stojetz et al., 2026). A household-level approach based on a household's own reported contact with climatic stressors within a defined recall period can capture these within-community differences.

For displaced populations, this issue is particularly relevant. Refugees' residential locations, shelter quality, and daily mobility patterns differ sharply from surrounding host communities, meaning that grid-cell or district-level exposure measures may misrepresent the climate conditions households actually experience.

Sensitivity. Most macro-level indices proxy sensitivity through administrative or census-based indicators such as poverty rates, population density, share of agriculture in employment, or infrastructure coverage at the district or national level (Hahn et al., 2009; Vincent, 2004). While these indicators capture important structural determinants, they mask the considerable within-area variation in the conditions that mediate how climate impacts translate into harm. For example, two households in the same district may occupy dwellings of vastly different quality; one with a reinforced roof and reliable water supply, the other with a corrugated-metal shelter and intermittent access to safe water. Yet both would be assigned the same sensitivity level in aggregate approaches.

For displaced populations, this problem is especially acute: refugee households often live alongside host communities but in fundamentally different housing, with different water and sanitation arrangements, and with different health profiles. Capturing sensitivity at the household level, through direct observation or survey measures of shelter conditions, water security, sanitation, and shock-absorption capacity, is therefore essential for meaningful vulnerability assessment in displacement settings.

Adaptive capacity. Standard vulnerability frameworks proxy adaptive capacity through structural indicators such as local poverty, infrastructure, or governance quality (Engle, 2011; Hahn et al., 2009; Vincent, 2004). While these factors are undeniably important, they capture only the material and institutional preconditions for adaptation. A growing body of evidence from behavioral economics demonstrates that decision-making under scarcity and uncertainty is shaped by cognitive and psychological factors that structural indicators do not capture (De Bruijn & Antonides, 2022; Haushofer & Fehr, 2014; Ronzani et al., 2018; Burlacu et al., 2022). Even two households with identical income and asset profiles may differ dramatically in their willingness to invest in protective measures, their capacity for long-term planning, or their understanding of climate risks.

In displacement settings, where prior trauma, information constraints, and institutional exclusion are pervasive, these behavioral dimensions of adaptive capacity may be especially consequential (Fransen et al., 2024). A vulnerability framework that ignores them risks misidentifying which households are least equipped to adapt.

The CVI addresses these three limitations simultaneously by moving the unit of analysis to the household and by measuring each component (exposure, sensitivity, and adaptive capacity) through household-level survey data, with the adaptive capacity pillar explicitly incorporating behavioral and cognitive indicators. The framework is designed to be general: it specifies what each component should measure in conceptual terms, while leaving the choice of specific survey instruments to the implementing context.

2.2 Index architecture

The CVI comprises three pillars, each measuring a distinct dimension of climate vulnerability at the household level.

Exposure captures the household's experienced contact with climatic stressors—such as extreme heat, flooding, storms, drought, and extreme cold—within a defined recall period. It encompasses both direct impacts (e.g., shelter damage from extreme weather) and the household's subjective assessment of impairment from climatic conditions. Expectations regarding future climate events are also included, on the grounds that anticipated exposure shapes current preparedness behavior. The framework relies on self-reported, experience-based exposure rather than remotely sensed hazard data. This is a deliberate design choice: self-reports capture climate conditions as filtered through the household's lived reality, including shelter quality, location within a settlement, and daily routines. As we demonstrate in the validation exercise (Section 4.3), self-reported exposure correlates strongly with objective measures of cumulative climate burden but diverges from anomaly-based shock indicators, suggesting that each captures a distinct and valuable dimension of climate risk.

Sensitivity reflects the degree to which exposure translates into harm, given the household's structural conditions. Two households in the same area may differ substantially in shelter quality, water access, and capacity to absorb shocks, yet be assigned the same sensitivity score in an aggregate index. Sensitivity indicators are largely observable and overlap with standard humanitarian needs assessments, facilitating integration with existing data collection systems.

Adaptive capacity represents the household's ability to anticipate, respond to, and recover from climate impacts. The CVI distinguishes between structural and behavioral components of adaptive capacity. Structural components, such as access to social safety nets, infrastructure, and services, are captured primarily in the sensitivity pillar, following established practice. The adaptive capacity pillar focuses on behavioral factors that shape how households process climate risk and act on available information and resources.

Risk preferences. Risk-averse households may underinvest in adaptive measures that involve uncertain payoffs, such as changing livelihood strategies, investing in shelter improvements, or migrating to less exposed locations. Conversely, moderate risk aversion can be protective by discouraging reckless exposure. The risk preferences are elicited here using the The "Bomb" Risk Elicitation Task (Crosetto & Filippin, 2011). The framework treats risk aversion as reducing adaptive capacity on the assumption that, in displacement contexts where proactive investment is needed, the constraining effect of high risk aversion dominates. However, the relationship is likely non-linear, and implementers should consider context-specific calibration.

Time preferences. Households exhibiting stronger present bias—a disproportionate preference for immediate over future payoffs—are less likely to invest in preparedness measures whose benefits materialize over time, such as shelter reinforcement, water storage, or livelihood diversification. Present bias is conceptually distinct from simple impatience (a high but time-consistent discount rate): present bias implies a self-control problem amenable to commitment devices, while high discounting implies that the expected returns to preparedness must be raised. The framework captures both through intertemporal choice tasks, while acknowledging that disentangling the two typically requires richer elicitation protocols than most humanitarian surveys allow.

Climate knowledge. Households with limited understanding of climate change—its causes, expected trajectory, and local manifestations—are less equipped to interpret early warning signals, evaluate risk information, or adopt evidence-based adaptive behaviors. Climate knowledge is therefore treated as a cognitive resource that enhances adaptive capacity.

Observed behavioral adaptation. Whether a household has actually changed its behavior in response to climate conditions (e.g., shelter repairs, water-saving measures, livelihood adjustments) is the most direct indicator of adaptive capacity in action. Because it reflects realized adaptation rather than latent capacity, this indicator receives the highest weight in the adaptive capacity sub-index.

Social trust. Trust in neighbors, community institutions, and service providers facilitates collective action, information sharing, and access to informal insurance mechanisms—all of which support adaptive capacity.

Each indicator within the three pillars is normalized to the unit interval [0, 1] using min–max scaling based on the observed sample distribution. Indicators within each pillar are combined as a weighted average, with weights reflecting the indicator's relevance to the underlying construct (see Section 3.3 for the specific weights used in the Jordanian application and Appendix A.1 for the full variable descriptions). The three resulting sub-indices—exposure, sensitivity, and adaptive capacity—form the inputs to the classification scheme described below.

2.3 Classification logic

The CVI classifies households into four vulnerability categories: Low, Stress, Crisis, and Emergency. The classification follows a hierarchical decision rule that establishes exposure as the primary gateway and then differentiates severity based on sensitivity and adaptive capacity.

The hierarchy reflects three principles. First, climate vulnerability, by definition, requires contact with climatic stressors. Households that are not exposed to climate hazards may face other forms of deprivation but are not climate-vulnerable in the specific sense the index is designed to measure. Exposure is therefore a necessary condition for classification above the lowest category.

Second, among exposed households, high sensitivity implies that climate impacts are already materializing—through shelter damage, health shocks, or water insecurity—representing acute, present-tense harm. High sensitivity combined with high exposure therefore defines the Crisis category.

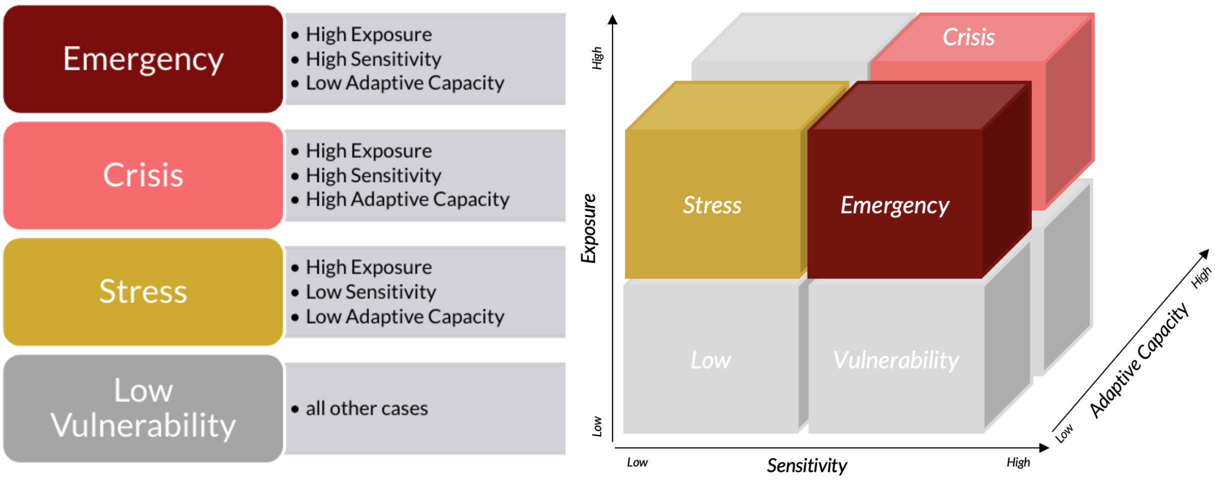
Third, low adaptive capacity among exposed households implies an elevated future risk that the household will be unable to respond to or recover from climate shocks, but does not necessarily indicate that impacts are currently materializing. High exposure combined with low adaptive capacity (but not high sensitivity) therefore defines the Stress category, which denotes elevated risk rather than active harm.

The Emergency category combines all three conditions: high exposure, high sensitivity, and low adaptive capacity. Households in this category face the most severe climate vulnerability, experiencing active harm from climate impacts while lacking the behavioral and cognitive resources to adapt. The detailed definitions of each category are provided in Appendix A.2.

The thresholds distinguishing "high" from "low" on each sub-index are defined relative to the sample distribution (e.g., above or below the median). This means that the CVI identifies the most vulnerable households within a given population rather than measuring vulnerability against an absolute, externally defined standard. This relative approach is well suited to targeting interventions within a specific operational context—such as a national refugee population—where the goal is to prioritize the most at-risk households for limited resources. However, it limits direct comparability across populations or time periods with different baseline distributions, and users should be aware that the shares of households falling into each category are partly a function of the distributional cutoff chosen. We test sensitivity to alternative threshold choices (terciles, 60th percentile) in the Appendix.

Figure 1. Climate vulnerability classification logic

a) Category definitions *b) Three-dimensional representation*



Note: The 3D figure in panel (b) illustrates how households are positioned within the multidimensional space defined by exposure, sensitivity, and adaptive capacity. Each household is classified according to its relative standing on these three components.

3 Empirical Application: Refugees in Jordan

3.1 Context: climate risks and displacement in Jordan

Jordan faces growing climate pressures (Binder et al., 2022). Over the past few decades, the country has encountered repeated periods of drought, flash floods, and landslides. The main weather events predicted to affect Jordan are recurring droughts, but also flash floods, landslides, and heatwaves (Farhan & Ayed, 2017; Binder et al., 2022). Climate models indicate a rise in the annual number of extremely hot days exceeding 35°C across the country (Binder et al., 2022). By the end of the century, densely populated areas in Northwest and West Jordan may experience up to 71 additional very hot days per year. These trends will compound Jordan's existing water scarcity—the country already ranks fifth globally in water stress (Hofste et al., 2019), and per capita water availability is projected to decline by approximately 75 percent relative to 2000 levels (Binder et al., 2022; UNDESA, 2006). The associated climate risks are expected to exacerbate existing vulnerabilities. Jordan's already strained resources and socio-economic challenges—water scarcity, fragile ecosystems, non-sustainable agriculture, high unemployment rates especially among women and youth, limited economic and political participation of women, and health issues (Al Qudah et al., 2021)—further complicate the country's capacity to adapt.

3.2 Data: the 2024 UNHCR Vulnerability Assessment Framework

We use the 2024 UNHCR Vulnerability Assessment Framework (VAF) for Jordan (UNHCR, 2024a, 2024b), which surveyed 5,164 refugee households (1,126 in camps; 4,038 in host communities) between September 2023 and January 2024. The survey is representative at the national level of the refugee population registered with UNHCR in Jordan. For the first time in 2023, the VAF included a dedicated climate module, covering self-reported experience with climatic shocks, impacts on assets and well-being, and behavioral responses.

3.3 Operationalization of the CVI

The operationalization of the CVI for the Jordanian application involves mapping the general framework described in Section 2 onto the specific variables available in the 2024 VAF. Table 1 summarizes the measurement domains and their VAF indicators. The full variable descriptions, rationales, and data sources for each sub-index are provided in Appendices A.1-A.3.

Table 1. Key measurement domains and VAF indicators

Domain	**Description**	**VAF indicators**
Exposure	Self-reported experience of climatic events (heatwaves, floods, droughts, extreme cold) and recent event frequency experienced by the household.	DamageDwellingFlood, DamageDwellingStorm, ImpairmentHeat, EventsExpectationHeat, EventsExpectationFlood, EventsExpectationDrought, EventsExpectationStorm, EventsExpectationCold
Sensitivity	Housing quality and materials, recent health shocks, water insecurity indicators, and dependence on climate-sensitive livelihoods.	NoWaterDrink, NoWaterOther, DwellingShock50, DwellingShock300, SocialSafetyNet, AirConditioningUsage, TypeOfShelter, RoofCondition, OpeningsConditions, ElectricalCondition, LightVentilationCondition, AccessToDwellingCondition, WaterSource, WaterReliability, WaterStorageCapacity, LatrineAccess, LatrineExclusiveUse, LatrineSafe, TypeOfWasteWater, FrequencySolidWaste, EnumeratorJudgement
Adaptive capacity	Behavioral indicators (risk attitude, intertemporal choice), climate knowledge items, observed behavioral change adoption, and social trust.	ClimateChangeKnowledge, ClimateChangeNow, ClimateChangeExpectation, ClimateChangeBehaviorChange, RiskAttitude, TimePreferences, SocialTrust

Several implementation choices regarding indicator weighting merit discussion. Within the exposure sub-index, indicators of direct impact—shelter damage from floods (weight: 2), shelter damage from storms (weight: 2), and impairment from heat (weight: 2)—receive double weight relative to expectation items (weight: 1 each), reflecting the judgment that experienced exposure is more informative about current vulnerability than anticipated future events. Within the sensitivity sub-index, air conditioning usage receives triple weight (weight: 3) because access to cooling is a particularly consequential moderator of heat-related harm in Jordan's climate; all other sensitivity indicators receive a weight of 1. Within the adaptive capacity sub-index, observed behavioral change (ClimateChangeBehaviorChange) receives the highest weight assigned to any single indicator in the index (weight: 4), on the grounds that realized adaptation is the most direct signal of adaptive capacity. The remaining behavioral indicators—risk attitude, time preferences, climate knowledge, climate change perception (current and expected), and social trust—each receive a weight of 1.

These weighting choices are informed by domain knowledge and the structure of the VAF questionnaire rather than derived statistically (e.g., through principal component analysis). We test sensitivity to alternative weighting schemes—equal weights across all indicators, and reduced weight on behavioral change—in the Appendix.

Normalization follows min–max scaling based on observed sample ranges. For each indicator, a reference point is defined representing the least vulnerable outcome (e.g., disposing wastewater through a network system rather than storing it in a plastic bag). Indicators are then rescaled so that 0 corresponds to the reference point and 1 to the maximum observed vulnerability. The following formula is used for normalization:

$$\text{score}_{standardised} = \frac{\text{raw } data - reference\ point}{baseline\ maximum - baseline\ minimum}$$

Sub-indices are computed as weighted averages of normalized indicators within each pillar using the following formula:

$$\text{score}_{sub-index} = \frac{(x_{i1}*W_1)+(x_{i2}*W_2)+(x_{i3}*W_3)+\ldots+(x_i*W_x)}{W_1+W_2+W_3+\ldots+W_x}$$

The classification of households into vulnerability categories follows the hierarchical logic described in Section 2.3, with the median of each sub-index serving as the threshold distinguishing "high" from "low." The complete step-by-step computation procedure, including data quality checks, reference point definitions, and aggregation rules, is documented in Appendix A.3.

3.4 Climatic shock indicators

To compare households' self-reported climate exposure against objective climatic conditions, we construct three external indicators of climate shocks covering the same twelve-month period prior to data collection (September 2022 to December 2023, with the baseline period 1991–2020). We focus on three types of shocks—extreme heat, heat-wave anomalies, and drought—each representing a distinct climatic stressor relevant for Jordan (Binder et al., 2022). All measures are constructed at the grid-cell level (~9 km resolution).

Extreme heat (days > 35°C). We measure the absolute burden of extreme heat using the number of days in which daily maximum temperatures exceeded 35°C, a widely used threshold for hazardous heat in the Middle East. Data come from ERA5-Land (hourly data aggregated to daily maxima; ~9 km resolution) (Muñoz-Sabater et al., 2021). We compute extremely hot days for each grid cell over the twelve-month period and merge them with household records.

Heat-wave anomalies. Short-term heat shocks are measured as deviations of recent monthly mean temperatures from their 1991–2020 climatological averages. We use ERA5-Land monthly aggregates (~9 km resolution) (Muñoz-Sabater et al., 2021) and compute monthly anomalies for each grid cell during the twelve-month window prior to interview. Positive departures indicate heat-wave conditions. These anomalies are then classified into four categories based on their magnitude in standard deviations: Extreme heat wave ($\geq 2\sigma$), Severe heat ($\geq 1.5\sigma$), Moderate heat ($\geq 1\sigma$), and No heat shock ($< 1\sigma$). Anomalies are calculated for each grid cell over the twelve-month period and compared with household records.

Drought shocks (SPEI). Hydro-climatic drought is captured using the twelve-month accumulated Standardised Precipitation–Evapotranspiration Index (SPEI), derived from the global SPEI dataset (0.5° resolution). The twelve-month SPEI reflects long-term water stress and is interpreted using standard thresholds (-1.0σ to -1.5σ moderate; -1.5σ to -2.0σ severe; $< -2.0\sigma$ extreme). We use grid-level SPEI values and compare them with household records.

3.5 National vulnerability mapping

To contextualize the household-level CVI, we compare it with the national vulnerability mapping developed by the Arab Water Council and the World Food Programme (WFP/AWC). Unlike our approach—which draws on microdata from the UNHCR VAF and is representative of registered refugee households in Jordan—the WFP/AWC product is a spatially aggregated assessment of the Jordanian territory. It combines gridded climatic hazards (e.g., Standardized Precipitation Index and Normalized Difference Vegetation Index anomalies, temperature extremes), land-use and population-exposure layers, and administrative socio-economic indicators into composite maps of exposure, sensitivity, adaptive capacity, and overall vulnerability using expert-assigned weights.

To move beyond a purely visual comparison, we quantify the association between the CVI and the WFP/AWC indices at the level of the grid cells in which VAF households are located, excluding grid cells with no refugee presence. We report Spearman rank correlations between each CVI sub-index and each WFP/AWC sub-index for this restricted sample (see Section 4.4).

4 Results

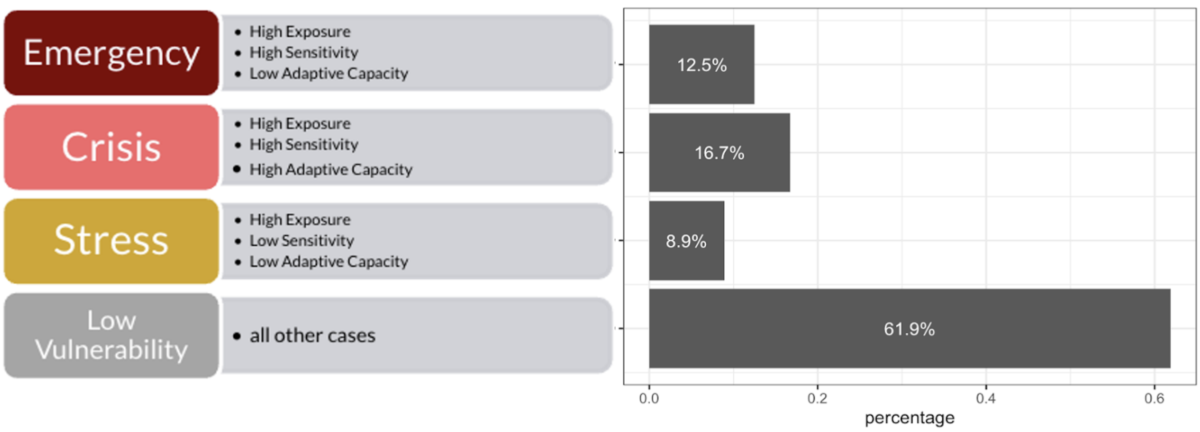
This section presents the distribution of climate vulnerability across refugee households in Jordan, describes patterns across camps and host communities, and a descriptive comparison between subjective and objective exposure measures. It concludes comparing the household-level CVI with an independent national vulnerability mapping.

4.1 Distribution of climate vulnerability

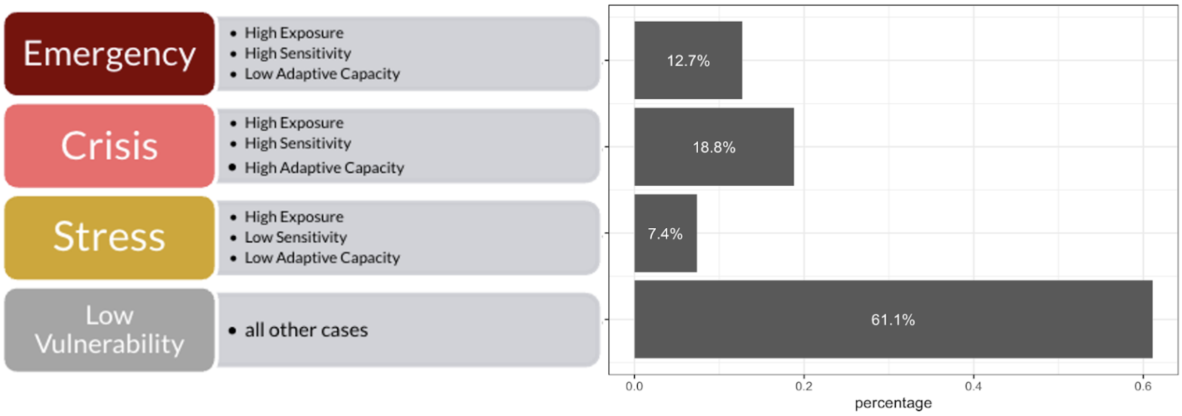
The CVI reveals substantial variability in climate vulnerability across refugee households. Figure 2 shows the weighted distribution of households across the four vulnerability categories: Low, Stress, Crisis, and Emergency.

Figure 2. Distribution of respondents in CVI categories

(a) Camps



(b) Host communities



Note: Logical definition of the four vulnerability categories and the weighted distribution of households across the categories for refugees living in camps (a) and host communities (b).

Across the full refugee population sampled through the VAF, approximately 40% of households fall into "concerning" categories (Stress, Crisis, Emergency). Roughly 10% are classified as Emergency, representing households simultaneously facing high exposure, high sensitivity, and low adaptive capacity. The remaining households are split between Low and Stress categories, reflecting moderate but non-negligible levels of vulnerability.

Analyses of heterogeneity based on household head gender, education, age, and household size reveal no large or systematic gender disparities in vulnerability classification after controlling for other factors. Neither age nor household size emerges as a consistent predictor of Emergency status once behavioral measures and structural controls are included in the model. Higher education is associated with modestly elevated adaptive capacity.

4.2 Differences between refugee camps and host communities

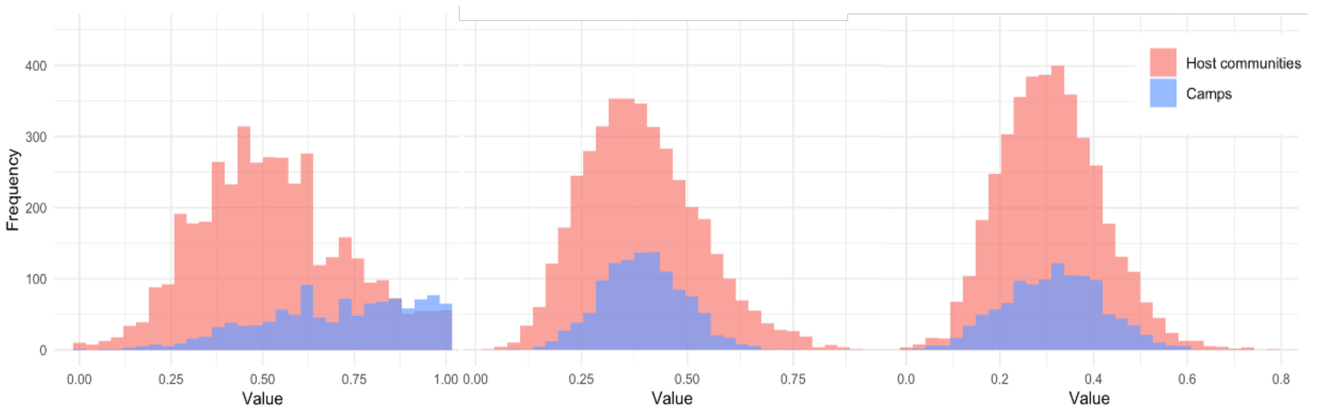
The results above are based on thresholds that are group-specific. When we apply the host-community thresholds to both refugees in host communities and camps, refugees in camps are substantially more vulnerable: slightly less than 40 percent of the refugee population in camps are classified in the relatively Low Vulnerability category. Notably, 18.5 percent fall into the most severe vulnerability category, the Emergency state, 28.6 percent into the Crisis state, and 14.7 percent into the Stress state.

Vulnerability profiles differ substantially between camp-based residents and refugees living within host communities (Figure 3). Households in camps—particularly in Zaatari—generally experience higher exposure, characterized by more uniform susceptibility to climatic hazards such as extreme heat, dust storms, and localized flooding. They also exhibit greater sensitivity, influenced by high shelter density, infrastructure limitations, restricted livelihood options, and a higher prevalence of chronic health conditions. Moreover, adaptive capacity—especially in economic terms—tends to be lower, with many households living in camps facing severe liquidity constraints and dependence on humanitarian assistance. Consequently, the proportion of households classified in the Emergency phase is markedly higher in camps, and the shares in Crisis and Stress categories also exceed those observed in host communities.

In contrast, refugee households in host communities display greater internal variation. Exposure levels differ considerably across governorates and neighborhoods, with some households reporting significant exposure to flooding or heat, while others experience minimal climatic risk. Sensitivity indicators also vary widely, reflecting disparities in housing quality, employment access, debt burdens, and household composition. Similarly, behavioral adaptive capacity spans a broad spectrum: some households show strong climate awareness and forward-looking planning behaviors, whereas others are constrained by present bias or limited adaptation practices. Despite this heterogeneity, host-community households on average demonstrate lower overall vulnerability than those in camps, though the distribution of vulnerability within host communities is more dispersed.

Figure 3. Camp vs host distributions of sub-indices

(a) Exposure *(b) Sensitivity* *(c) Adaptive capacity*

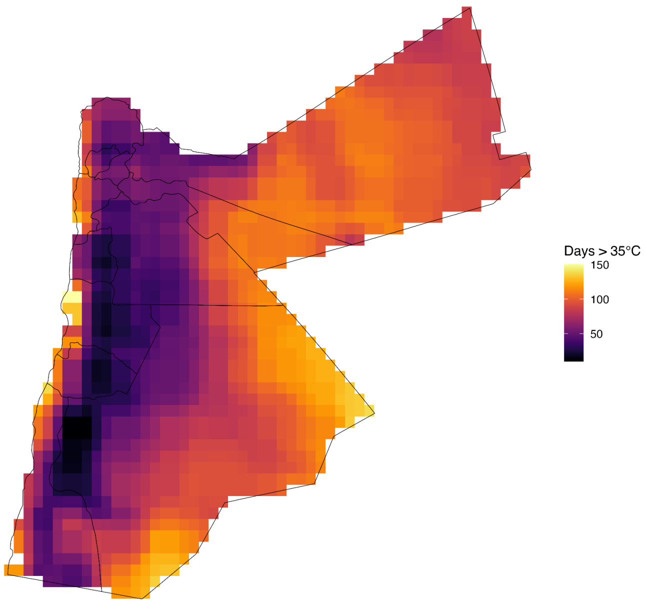


Note: The figure shows a rightward shift in the distribution of exposure among camp-based refugees relative to those in host communities, reinforcing that camp residents face substantially greater exposure to climate shocks.

4.3 Comparing household exposure and objective climatic shocks

We compare the household-level exposure index with three objective climatic indicators constructed for the same twelve-month period preceding each interview. The results reveal a clear distinction between associations with absolute climatic conditions and those with anomaly-based shock measures.

Figure 4. Number of days exceeding 35°C (September 2022 to January 2024)



Note: Cumulative number of days exceeding 35°C for each grid cell between September 2022 to January 2024. ERA5-Land (hourly data aggregated to daily maxima; ~9 km resolution) for the country of Jordan.

Self-reported exposure aligns strongly with absolute measures of climatic stress. Households residing in areas experiencing a higher cumulative heat burden (see Figure 4) report significantly greater exposure: the exposure index is strongly and positively correlated with the number of days exceeding 35°C ($r = 0.728$). This indicates that households located in persistently hotter areas perceive and report higher levels of climate-related exposure. A similar, though weaker, pattern emerges for moisture conditions. Using 12-month SPEI values, which ranged from 0.19 to 0.52 during the study period (i.e., entirely within the "normal" moisture regime), we find a statistically significant negative correlation between SPEI and household exposure ($r = -0.107$, $p < 0.001$). Linear regression results indicate that a one-unit increase in SPEI is associated with a 0.197 decrease in the exposure index ($R^2 = 0.012$), suggesting that households in relatively drier locations experience marginally higher exposure even in the absence of drought conditions.

By contrast, self-reported exposure does not align with anomaly-based shock indicators. Despite accurate spatial matching between households and ERA5-Land grid cells, households classified as experiencing heat-wave shocks report lower exposure levels than those without such shocks. Specifically, households in areas classified as experiencing moderate heat shocks exhibit exposure indices that are, on average, 0.036 points lower than households in areas without heat shocks (95% CI: −0.052 to −0.021; $t = 4.609$; $p < 0.001$). Consistent with this pattern, exposure is negatively correlated with heat anomaly z-scores ($r = -0.114$; 95% CI: −0.144 to −0.083; $p < 0.001$).

Drought shock indicators show no meaningful correspondence with self-reported exposure. All households experienced normal moisture conditions during the twelve months preceding the survey, and no severe, or extreme drought events were recorded. While small gradients in exposure are observable across SPEI quartiles, effect sizes are modest and explained variance remains low.

Taken together, these results indicate that household-reported exposure reflects persistent climatic conditions, such as chronic heat and relative dryness, rather than short-term departures from historical baselines. The divergence between experience-based exposure and anomaly-based shock measures underscores the distinction between lived climate stress and hazard-defined shocks, reinforcing the value of household-level data for capturing climate vulnerability in humanitarian settings.

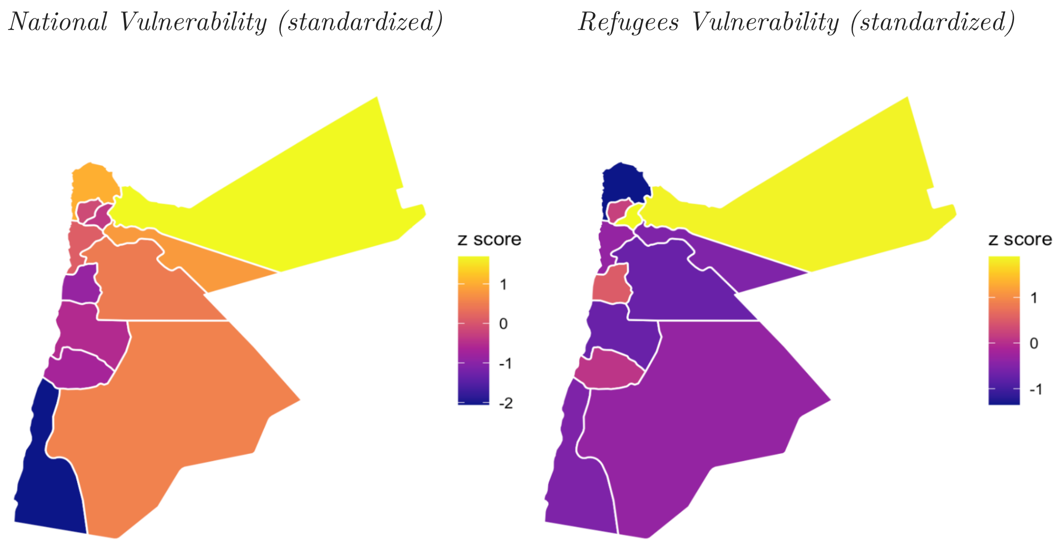
4.4 Comparison with national vulnerability mapping

To situate the household-level CVI within broader national assessments, we compare it to the vulnerability mapping developed by the Arab Water Council and the World Food Programme (WFP/AWC). Overall, the association between our CVI and the WFP/AWC sub-indicators is weak (see Figure 5). This partial alignment is expected given several structural differences between the two approaches.

First, the two instruments target different populations: the national maps describe vulnerability in the general population, while our CVI focuses specifically on registered refugees, whose socio-economic profiles and spatial distribution—particularly the concentration in camps and select host communities—differ markedly from national averages.

Second, the unit of analysis varies. Our CVI captures household-level heterogeneity, whereas the WFP/AWC framework aggregates information to grid cells or administrative districts, smoothing local disparities that are central to refugee vulnerability.

Figure 5. Comparison between national and refugees vulnerability mapping



Note: Both measures were standardized to z-scores to allow direct visual comparison. The National (WFP/AWC) indices are gridded/district measures based on multi-year climatologies and administrative aggregates (see WFP/AWC methodology and Table 8 for expert weights); our CVI is a household-level index derived from the UNHCR VAF survey of registered refugee households (survey year 2023).

Third, exposure is conceptualized differently. The national mapping relies on multi-year climatological baselines and objective hazard layers, while our exposure dimension reflects recent, experience-based shocks reported by households.

Fourth, the content of the adaptive-capacity dimension diverges. Our CVI incorporates behavioral and cognitive factors—such as risk and time preferences and climate knowledge—absent from the WFP/AWC index, which emphasizes structural and environmental characteristics (e.g., infrastructure, poverty, groundwater stress).

Fifth, the weighting and scaling schemes differ. The WFP/AWC maps classify indicators into discrete vulnerability categories and apply expert-derived weights, whereas our CVI combines continuous, standardized variables using equal weights across components.

Finally, the temporal reference frames do not fully align: the WFP/AWC maps draw on census and administrative data from earlier years and climatological means from 1981–2010, while our survey captures contemporaneous household conditions and recent shock experiences.

These differences in population coverage, spatial scale, exposure definition, indicator content, weighting, and temporal reference naturally limit the degree of alignment between the two indices. Rather than indicating inconsistency, the divergences underscore the complementarity of the two approaches: national mapping offers a macro-level overview of structural and environmental vulnerability, while household-level data reveal the lived experiences and behavioral dimensions that remain invisible in aggregated assessments.

5 Discussion

This paper has pursued two objectives: developing a general, household-level framework for climate vulnerability measurement that integrates behavioral adaptive capacity, and applying that framework to produce the first behaviorally informed vulnerability profile of a national refugee population. We discuss each in turn before addressing limitations and implications.

The CVI framework advances existing vulnerability measurement in three respects. First, by moving the unit of analysis from aggregate levels, such as nations, districts or grid cells, to the household, it captures within-community heterogeneity in exposure, sensitivity, and adaptive capacity that aggregate indices obscure. Second, by incorporating behavioral indicators (risk preferences, time preferences, climate knowledge, and observed adaptive behaviors) it measures a dimension of adaptive capacity absent from standard indices, which rely on structural proxies such as income, assets, or infrastructure. Third, by organizing the three sub-indices through a transparent hierarchical classification, the framework yields four operationally relevant categories (Low, Stress, Crisis, Emergency) that can directly inform humanitarian targeting. These features are not specific to the Jordanian application: the framework requires only that implementing surveys include modules on climate exposure, housing and livelihood conditions, and a small set of behavioral elicitation tasks. Such modules can be integrated into existing humanitarian assessment instruments, such as UNHCR's VAF, WFP's Comprehensive Food Security and Vulnerability Analyses, or IOM's Displacement Tracking Matrix, at modest additional cost. Future applications should test whether the behavioral indicators that prove most informative in Jordan, particularly observed behavioral change and time preferences, retain their important role in other displacement contexts, from protracted urban displacement in East Africa to camp settings in South and Southeast Asia.

The empirical application to Jordan reveals three substantive findings. First, climate vulnerability among registered refugees is widespread: approximately 40 percent of households fall into concerning categories, and roughly 10 percent are classified as Emergency, simultaneously facing high exposure, high sensitivity, and low adaptive capacity. Second, camp-based refugees exhibit systematically higher vulnerability than those in host communities across all three sub-indices. This pattern likely reflects structural conditions: camp residents face greater mobility restrictions, depend more heavily on humanitarian transfers, and live in more uniform and exposed shelter environments. Host-community refugees, by contrast, show greater variation in both material conditions and behavioral capacities, producing a wider spread in CVI scores. Third, the comparison of self-reported exposure with objective climatic indicators reveals that household reports capture cumulative climate burden rather than short-term anomalies; self-reported exposure correlates strongly with absolute heat burden but not with deviation-based shock measures. This pattern is not a limitation of self-reports but an indication that lived climate experience can integrate over time, reflecting sustained, place-based environmental conditions rather than statistical deviations from historical baselines. Objective and subjective measures therefore capture distinct and complementary dimensions of climate risk; integrating both is essential for a complete picture, especially for displaced populations whose risk perceptions may be shaped by prior trauma, limited information access, or heightened environmental sensitivity.

The comparison with the WFP/AWC national vulnerability mapping reinforces this complementarity at a different scale. The partial alignment between the two instruments reflects systematic differences in population coverage, spatial resolution, indicator content, and temporal reference. Rather than indicating inconsistency, these divergences underscore the value of combining macro- and micro-level assessments: national maps identify high-risk regions, while household-level indices identify the most vulnerable individuals within those regions.

Several limitations should be noted. First, self-reported exposure may be subject to recall bias or influenced by subjective perception; however, the strong correlation with objective measures of cumulative heat burden provides reassurance that self-reports contain substantial valid signals. Second, the analysis is cross-sectional and does not identify causal pathways from behavioral traits to vulnerability outcomes. The behavioral indicators in the CVI should therefore be interpreted as diagnostic markers of constrained adaptive capacity rather than as causal drivers. If we assume that risk preferences or present bias can be molded, these shifts could potentially improve adaptive capacity; posing an empirical question requiring longitudinal or experimental evidence. Third, the empirical application is focused on refugees registered with UNHCR in Jordan; unregistered refugees, migrant workers, and vulnerable Jordanian households are not included. Fourth, the weighting of indicators within sub-indices is informed by domain knowledge rather than derived statistically. Future work should test sensitivity to alternative weighting schemes.

The findings carry several implications for policy and practice. Humanitarian actors can use household-level CVI measures to prioritize households for anticipatory cash transfers, shelter upgrades, water assistance, or climate-resilient livelihood support. The behavioral component adds specific diagnostic value: households with low adaptive capacity driven by present bias or limited climate knowledge are candidates for behaviorally informed interventions — commitment savings devices, simplified climate information, or planning prompts — rather than (or in addition to) standard material transfers. More broadly, the analysis suggests that effective climate adaptation programming in displacement settings requires attention not only to what resources households have, but to how they make decisions about using them.

6 Conclusion

This paper introduces a household-level Climate Vulnerability Index that integrates behavioral adaptive capacity into the established exposure–sensitivity–capacity framework, and applies it to the 2024 UNHCR Vulnerability Assessment Framework for refugees in Jordan.

Two main conclusions emerge. First, the CVI framework demonstrates that behavioral dimensions (risk preferences, time preferences, climate knowledge, and observed adaptive behaviors) add meaningful diagnostic content to climate vulnerability assessment beyond what structural indicators alone provide. The weak overall correspondence between the CVI and the structurally oriented WFP/AWC national mapping, driven in part by the behavioral content unique to the CVI's adaptive capacity sub-index, suggests that these factors capture a dimension of vulnerability that aggregate assessments miss. Second, applying the framework to Jordan reveals that climate vulnerability among refugees is widespread and sharply differentiated by residential setting, with camp-based households facing compounded disadvantage across all three vulnerability dimensions.

The framework is designed to be replicable. Future work should apply the framework in other displacement and non-displacement contexts to further assess the generalizability of our findings from refugees in Jordan and to better understand the interaction between behavioral traits and structural constraints in shaping climate vulnerability. The framework offers a practical tool for humanitarian agencies seeking to integrate climate risk into targeting, early warning, and resilience programming.

Data statement

Data is available (from the UNHCR Operational Data Portal https://data.unhcr.org/)

Funding statement

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Competing interests statement

The authors declare no competing interests.

Declaration of generative AI in the manuscript preparation process

During the preparation of this work the authors used Claude, GPT-5 and DeepWrite in order to expand the search for relevant material and revise the text of the manuscript. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Authors' contribution

PR, SF, SH, WS: Conceptualization, methodology, writing original draft, writing review & editing, supervision, and validation. PR, SF: Data curation, formal Analysis. WS: Funding acquisition. All authors had access to the data in the study and accepted responsibility to submit for publication.

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Appendix

A.1 Sub-index details

A1.1 Exposure

Description: The exposure sub-index reflects the extent to which a household is exposed to different types of climate hazards. Variables measuring individual households' exposure are retrieved by asking for example whether households experienced damage to their shelter due to extreme weather or whether they feel generally impaired by increasing temperatures. Household's expectations regarding future climate events are also enquired here.

Rationale: Household's exposure to climate change is decisive in our measure of vulnerability. The vulnerability of families not exposed to any climatic changes cannot be attributed to climate change. Therefore, high exposure is a precondition for our Climate Vulnerability Index. Sensitivity and adaptive capacity are negatively influenced by high exposure, as exposure can both increase sensitivity and erode adaptive capacity.

Variables for Calculation: DamageDwellingFlood, DamageDwellingStorm, ImpairmentHeat, EventsExpectationHeat, EventsExpectationFlood, EventsExpectationDrought, EventsExpectationStorm, EventsExpectationCold

Weighted Variables: DamageDwellingFlood (Weight: 2), DamageDwellingStorm (Weight: 2), ImpairmentHeat (Weight: 2)

Data Source: UNHCR VAF Jordan Survey

A1.2 Sensitivity

Description: The sensitivity sub-index refers to the degree to which exposure to climate hazards and other stressors related to climate change affects a household. Therefore, relevant socio-demographic and economic variables are answered, as well as the ability to respond to shocks induced by climate events.

Rationale: Sensitivity can increase a household's vulnerability. A highly sensitive household will be severely impacted by climate change, particularly when living in dire conditions already.

Variables for Calculation: NoWaterDrink, NoWaterOther, DwellingShock50, DwellingShock300, SocialSafetyNet, AirConditioningUsage, TypeOfShelter, RoofCondition, OpeningsConditions, ElectricalCondition, LightVentilationCondition, AccessToDwellingCondition, WaterSource, Waterreliability, WaterStorageCapacity, LatrineAccess, LatrineExclusiveuse, LatrineSafe, TypeOfWasteWater, FrequencySolidWaste, EnumeratorJudgement

Weighted Variables: AirConditioningUsage (Weight: 3)

Data Source: UNHCR VAF Jordan Survey

A1.3. Adaptive capacity

Description: The adaptive capacity indicator measures a household's internal capacity to adjust and adapt to climate change with minimal disruption, such as via asset transfers, behavioral shifts, social networks, or migration; as well as external factors determining a household's ability to adapt, such as the availability of services, resources, technology, governance, and institutions that support household-level adaptation. These are measured for example by a household's knowledge or perception of climate change, or behavioral indicators such as individuals' risk attitude or social trust.

Rationale: Adaptive capacity can mitigate risks stemming from individual exposure or sensitivity and can potentially reduce vulnerability, when households are highly capable of adapting to changing circumstances.

Variables for Calculation: ClimateChangeKnowledge, ClimateChangeNow, ClimateChangeExpectation, ClimateChangeBehaviorChange, RiskAttitude, Time Preferences , SocialTrust

Weighted Variables: ClimateChangeBehaviorChange (Weight: 4)

Data Source: UNHCR VAF Jordan Survey

A.2 Climate Vulnerability Categories

To identify different levels of vulnerability, we define four categories of vulnerability: Emergency, Crisis, Stress, and Low Vulnerability.

Emergency. Households in the Emergency category are the most vulnerable. They experience high levels of exposure and sensitivity, coupled with low adaptive capacity.

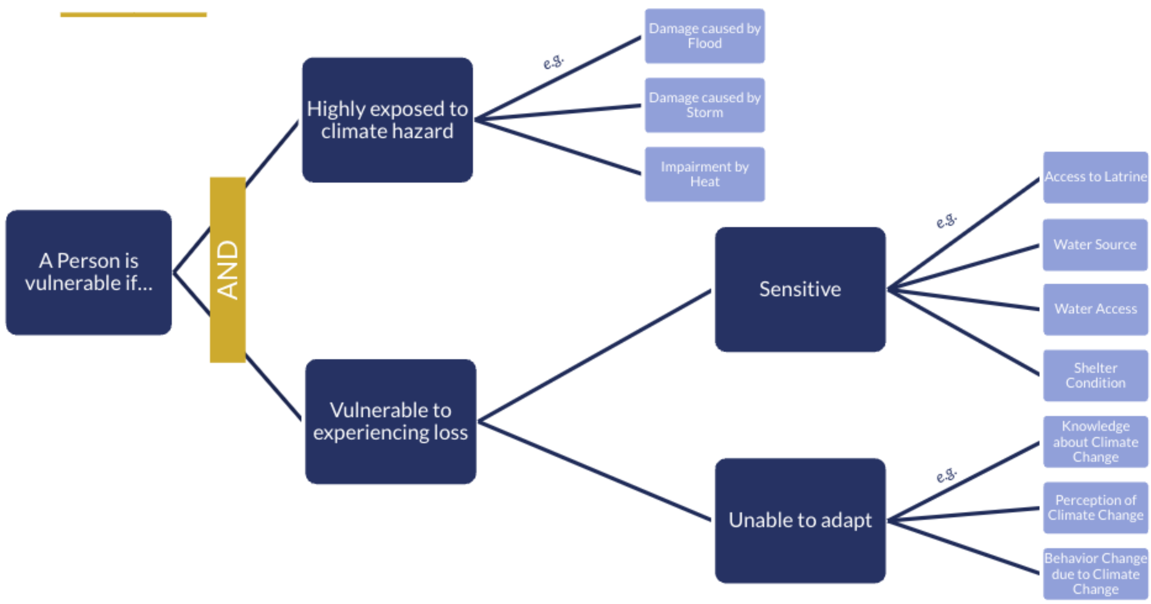
Crisis. Households in the Crisis category are still highly vulnerable. They experience high exposure and high sensitivity, however are more able to cope with the changing conditions and can adapt to the situation.

Stress. Households in the Stress category are moderately vulnerable. They are highly exposed to climate change, but less sensitive to climatic stress. Nevertheless, they are also rarely capable of adapting to climatic change.

Low Vulnerability. In the category of Low Vulnerability, all other cases are included. Households in this category experience relatively lower vulnerability to climate change, compared to the rest of the population.

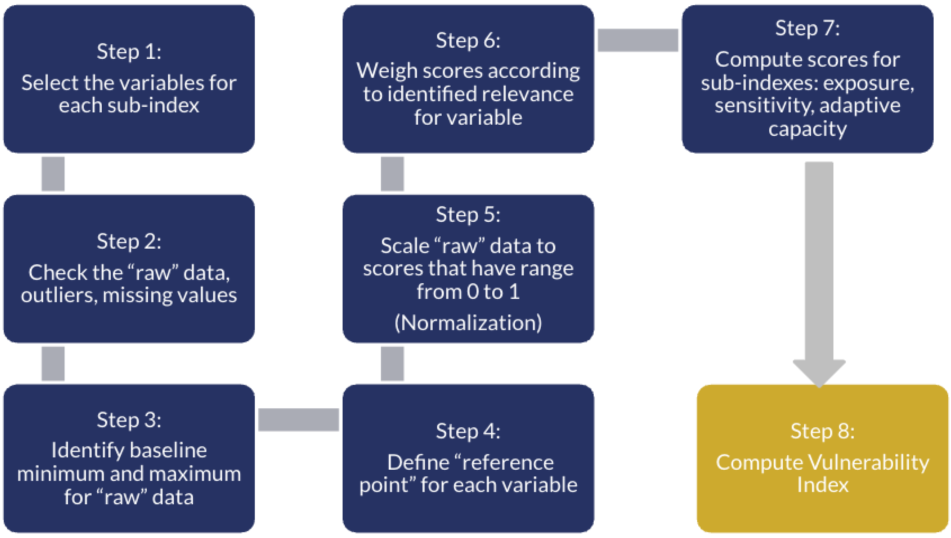
Our approach establishes an implicit hierarchy among the three sub-indices, with exposure as the most important, followed by sensitivity and adaptive capacity. To fall into categories above the lowest category, households must experience high exposure, making it the primary determinant. High sensitivity comes second in the hierarchy and, combined with high exposure, places households in the Crisis category. This is because we consider households with both high exposure and sensitivity in greater and more immediate distress (i.e. Crisis status) than those with high exposure and low adaptive capacity that can at least benefit from having better resources (i.e. Stress status).

Figure A.1. Climate vulnerability logic



A.3. Methodology – CVI Index Calculation

Figure A.2. Analytical steps for the index computation



Step 1: Select the variables for each sub-index.

Step 2: Subsequently, basic checks of the "raw" data, such as plotting distributions and ensuring the right handling of e.g. outliers or missing values, are conducted. Before conducting any other steps of the analysis we remove all missing values. If variables are not already in the correct format, they must be re-coded to numeric values, with ascending values denoting increased vulnerability.

Step 3: Based on the range of the distribution of each variable, the baseline minimum and maximum values are determined. Notably, this is based on the observed distribution of the variables in the sample, rather than on all possible response options.

Step 4: A reference point is defined for each indicator. This is the "ideal" point for each variable, meaning the value which describes the least vulnerable category associated with the respective variable, and therefore the most desirable outcome. Most reference points can be defined as logical points based on common-sense considerations. For example, disposing wastewater through a network system is more desirable than storing wastewater in a plastic bag, as it is easier, more hygienic, and comes with less health risks. Therefore, the answer option network system would be the reference point in this case.

Step 5: The data is normalized to range from zero to one, to allow easier comparability of the variables, for example: EnumeratorJudgement ranging from zero to three, based on the number of answer options, becomes zero to one. Our standardization involves the values determined in steps 3 and 4. The following formula is used to perform the standardization:

$$\text{score}_{standardised} = \frac{\text{raw } data - reference\ point}{baseline\ maximum - baseline\ minimum}$$

Step 6: As the variables are not equally informative to the level of climate vulnerability, we accordingly assign weights to variables. This allows us to adjust for a logical hierarchy in our set of variables (see the weights described in Section 3.3 and Appendix A.1). For example, we put more relative weight on experiencing damage by extreme weather events than on the expectation of an event in the exposure sub-index. Similarly, Air Conditioning Usage receives more weight in the Sensitivity category, as well as total behavior change related to climate change in the adaptive capacity sub-index. The corresponding weights are presented in Appendix A2.

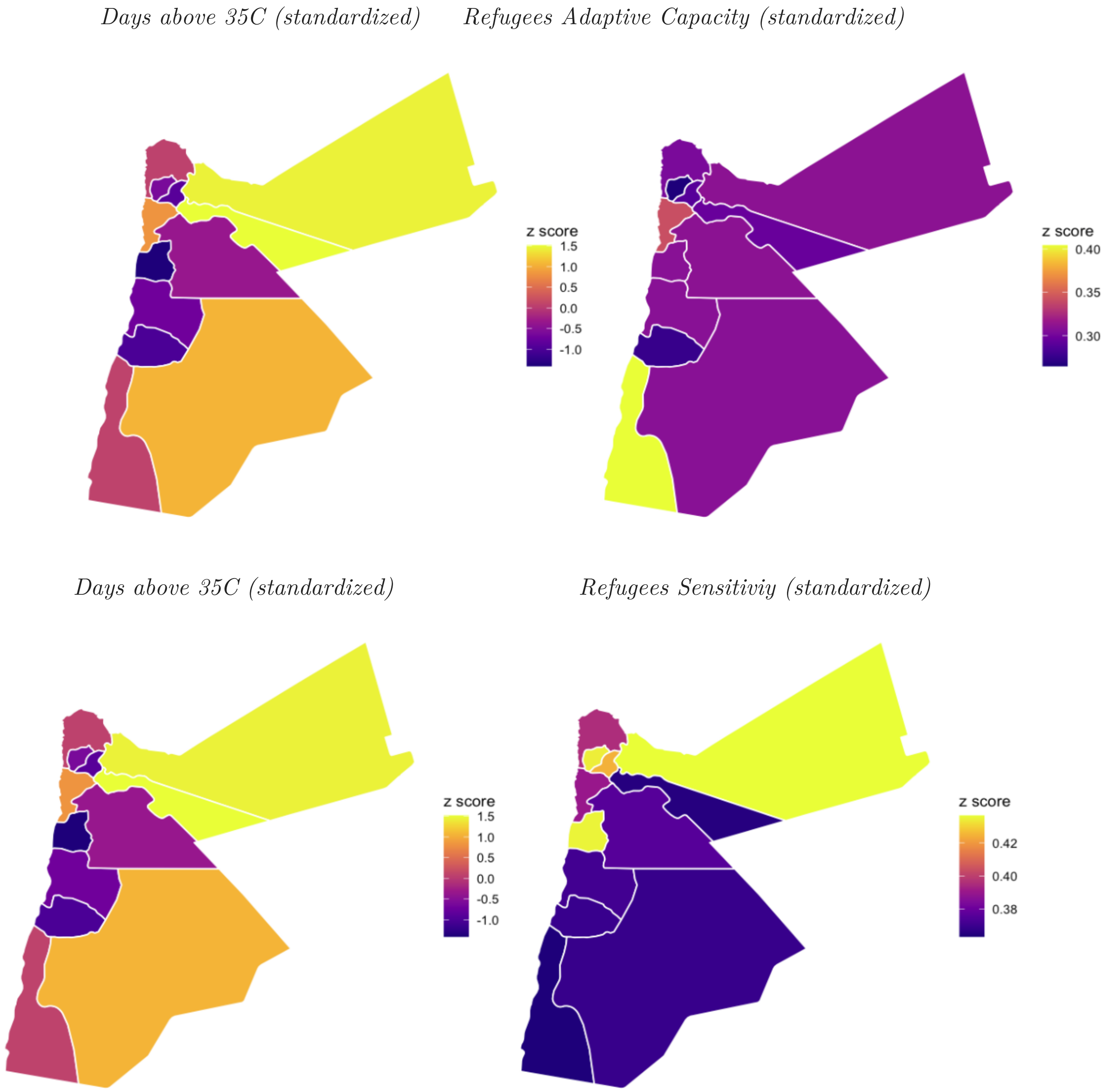
Step 7: The scores for the sub-indices are computed. Therefore, the standardized, weighted values of each variable included in the sub-index are summed up and subsequently divided by the weighted number of variables included. The following formula is used to calculate the sub-indices:

$$\text{score}_{sub-index} = \frac{(x_{i1} {}^* W_1) + (x_{i2} {}^* W_2) + (x_{i3} {}^* W_3) + \ldots + (x_i {}^* W_x)}{W_1 + W_2 + W_3 + \ldots + W_x}$$

Step 8: In a final step, the CVI is built, by creating a new variable that entails the different vulnerability categories according to households' levels of exposure, sensitivity, and adaptive capacity. Therefore, households with high exposure and sensitivity (above the median) and low adaptive capacity (below the median), are grouped in the Emergency category with the highest numeric value (4). Similarly, households with high scores for all three sub-indices are grouped in the Crisis group (3), while households with high exposure, but low sensitivity and adaptive capacity are grouped in the Stress category (2). All other cases are represented by the Low Vulnerability category (1).

A.4. Additional Figures

Figure A.3. Number of days above 35°C (September 2023-January 2024) and CVI sub-indexes



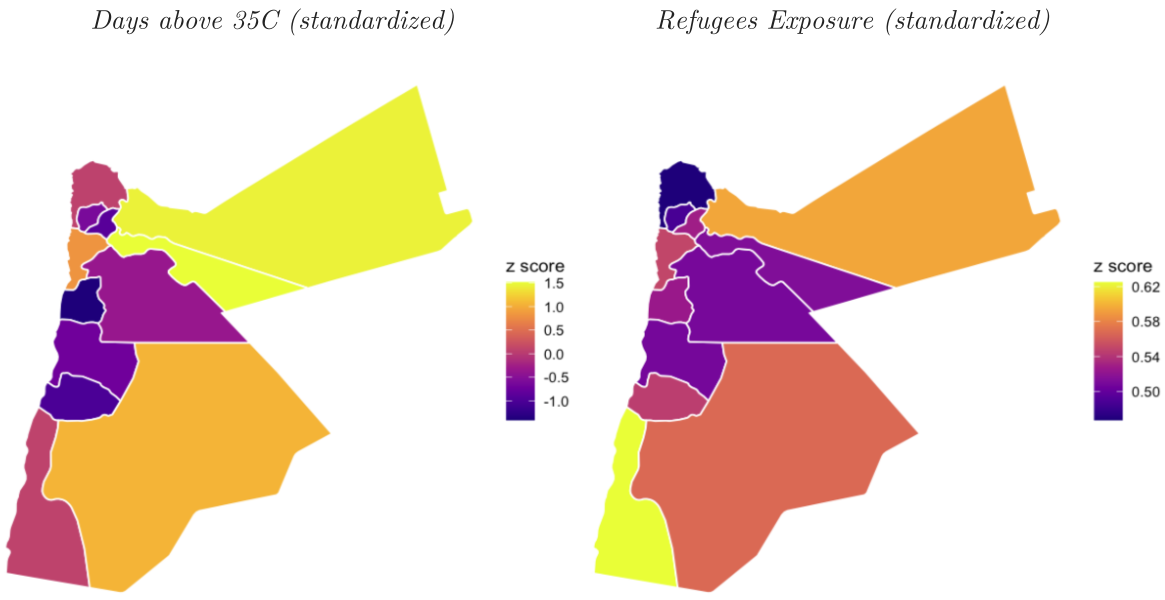


Figure A.4. Number of days above 35°C (September 2023-January 2024)

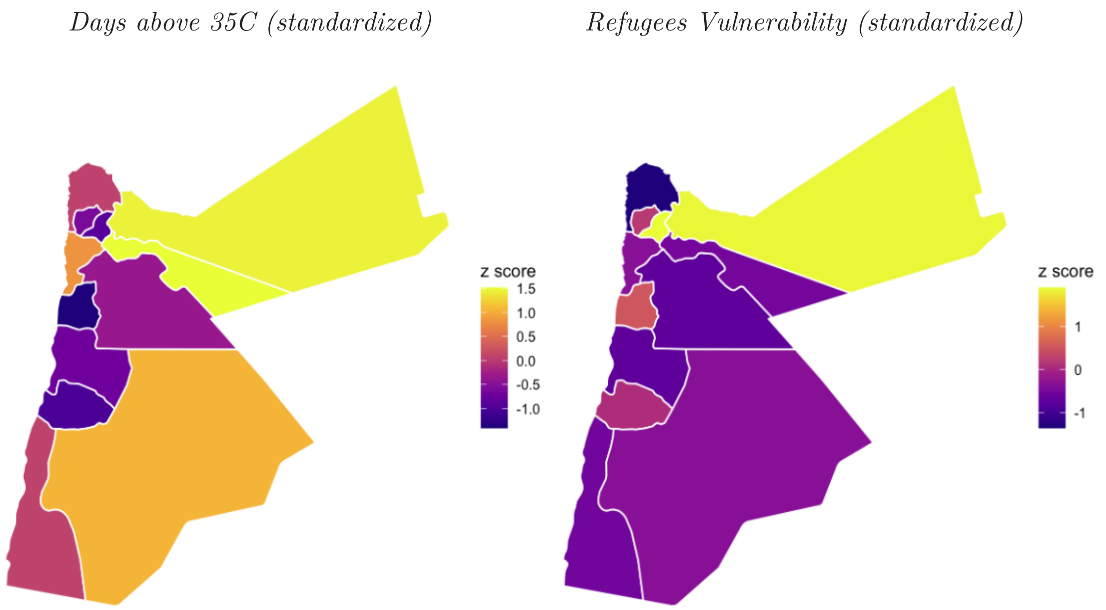


Figure A.5. National and Refugees sub-indexes comparisons