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The Making of a Non-parametric Multi-shock Index (MSI)

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Abstract

Households in low- and middle-income countries increasingly face overlapping economic, climatic, health, and conflict-related shocks that jointly erode welfare and food security. Yet many empirical and operational tools still measure shocks one at a time or aggregate them using ad hoc rules that assume equal severity and linear effects. This paper proposes a non-parametric multi-shock index (MSI) that summarizes household exposure to multiple shocks using an assumption-light, data-driven approach. The MSI construction proceeds in two steps: (i) shocks are empirically filtered based on their observed negative association with food security outcomes (anchored to the Food Consumption Score), and (ii) retained shocks are aggregated using alternative weighting schemes, including unweighted, population-weighted, and prevalence-weighted variants. We validate the MSI using multiple food security measures—Food Consumption Score (FCS), Reduced Coping Strategy Index (rCSI), Food Insecurity Experience Scale (FIES), and Household Dietary Diversity Score (HDDS). An application using FAO's Data in Emergencies (DIEM) household survey for Nigeria illustrates the approach and shows that cumulative exposure—especially systemic and compound exposure—is strongly associated with deteriorating food security outcomes. Among tested variants, the prevalence-weighted MSI provides the clearest discriminatory power and distributional sensitivity, supporting its use for targeting, monitoring, and shock-responsive programming (FAO, 2016; Maxwell et al., 2014; World Bank, 2018).

Keywords: Shock, index, food security, resilience, non-parametric, vulnerability

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1. Introduction

Households rarely experience shocks in isolation. Economic disruptions, climate variability, health events, and insecurity often co-occur and interact, producing cumulative impacts that exceed what single-shock frameworks can capture. This compounding reality is increasingly central to vulnerability analysis and shock-responsive policy design, particularly in low- and middle-income countries where exposure is high and formal insurance is limited (Adger, 2006; Birkmann et al., 2013; Heltberg et al., 2009). Yet much of the applied literature and many operational monitoring systems continue to measure shocks separately or rely on simple counts or parametric weighting schemes that implicitly assume equal severity, additivity, or stable functional forms across contexts. These simplifying assumptions can mischaracterize risk gradients and lead to under-targeting of households facing multi-dimensional stress.

This paper contributes a practical alternative by introducing a non-parametric multi-shock index (MSI) designed to be transparent, empirically anchored, and feasible for routine use with standard household survey shock modules. Rather than selecting shocks based on arbitrary prevalence thresholds or imposing parametric structure, the MSI uses a data-driven filtering step that retains only those shock indicators that demonstrate a statistically meaningful negative relationship with food security outcomes. The retained shocks are then aggregated under alternative weighting schemes, including unweighted, population-weighted, and prevalence-weighted variants, allowing the index to remain operationally flexible while preserving interpretability for policy use. This approach aligns with the growing emphasis on tools that support shock-responsive social protection, resilience monitoring, and early warning systems (FAO, 2016; Maxwell et al., 2014; World Bank, 2018).

We demonstrate and validate the MSI using FAO's Data in Emergencies (DIEM) household survey in Nigeria, a setting characterized by intersecting climatic, economic, and security stressors. Nigeria is used here as an empirical application to test whether multi-shock measurement improves our ability to diagnose vulnerability and to discriminate among food security outcomes. Using multiple indicators, including Food Consumption Score (FCS), Reduced Coping Strategy Index (rCSI), Food Insecurity Experience Scale (FIES), and Household Dietary Diversity Score (HDDS), the results show that cumulative and compound exposure is strongly associated with deteriorating food security, and that a prevalence-weighted MSI performs particularly well in distinguishing households along the vulnerability gradient.

Food security indicators provide a useful validation framework for shock measurement. Established metrics like the Food Consumption Score (WFP, 2008), Household Dietary Diversity Score (FAO, 2011), Reduced Coping Strategy Index (Maxwell & Caldwell, 2008), and Food Insecurity Experience Scale (FAO et al., 2023) capture complementary dimensions of dietary adequacy, behavioral response, and subjective experience. Empirical studies consistently show that exposure to climatic and economic shocks is associated with declining dietary diversity, increased negative coping, and heightened food insecurity (Headey & Ruel, 2020; Maxwell et al., 2014). However, much of this literature examines shocks in isolation rather than as interacting or compounding phenomena.

The growing recognition of compound and cascading risks underscores the need for measurement tools that reflect cumulative exposure. Climate science literature increasingly documents compound events—such as droughts coinciding with heatwaves or price spikes—whose joint effects exceed the sum of individual impacts (IPCC, 2022). In fragile and conflict-affected settings, these dynamics intersect with market disruptions and institutional fragility, amplifying welfare losses (FAO et al., 2023).

In response to these gaps, this paper develops a non-parametric multi-shock index (MSI) that aggregates empirically validated shocks into a composite measure of household exposure. The approach emphasizes three principles: (i) impact-based shock selection anchored to observed food security outcomes; (ii) transparent aggregation using alternative weighting schemes; and (iii) operational scalability for real-time monitoring and adaptive social protection systems (World Bank, 2018). We demonstrate and validate the MSI using nationally representative microdata from Nigeria—a context characterized by overlapping climate, economic, and conflict-related shocks—but the methodological framework is designed to be transferable across diverse risk environments.

By bridging conceptual advances in vulnerability theory with a practical, outcome-anchored measurement tool, the MSI contributes to the broader literature on resilience analytics and shock-responsive social protection. It offers a scalable framework for diagnosing compound vulnerability and informing early warning, targeting, and resilience-building interventions in multidimensional risk settings. In doing so, it advances the state of practice in vulnerability diagnostics and contributes to a growing literature on shock-responsive social protection and resilience analytics in low- and middle-income countries (FAO, 2016; World Bank, 2018; Maxwell et al., 2014).

2. Methodology

The construction of the MSI involves a critical rethinking of how shocks are aggregated and weighted, with a specific focus on their relationship to food security outcomes. This methodological refinement ensures that only empirically relevant and statistically robust indicators are used, thereby enhancing the reliability of the resulting index for programming and policy purposes.

The first stage of the process begins with the identification of shocks experienced by households. These shocks, such as sickness, drought, conflict, and economic hardship, are captured as binary variables in the dataset. However, unlike earlier approaches that treated all shocks equally or selected them based solely on prevalence thresholds, our proposed method incorporates a data-driven filter based on the Food Consumption Score (FCS). For each shock s_i, the sample is split into two groups: households that experienced the shock and households that did not. The mean FCS for each group is computed:

$$FCS_{shock} = E[FCS \mid s_i = 1], FCS_{nonshock} = E[FCS \mid s_i = 0]$$

The difference is used to assess the effect of each shock on food security. Only shocks with a statistically significant negative association with FCS—determined through mean comparisons and t-tests—are retained for inclusion in the index. This filtering step aligns the index with impact-based selection rather than arbitrary thresholds. This is an empirical filtering criterion grounded in the theoretical linkage between shocks and welfare outcomes (Devereux, 2001).

To account for household-level representativeness, a population-weighted version of each shock component is computed by multiplying the shock with the household survey weight variable w_i:

$$shock^{c}_{popwt} = w_i \times shock^{c}$$

As an alternative approach, shock prevalence[1] can be used to weigh each component by the relative frequency of the shock category π_c across the population, resulting in a prevalence-weighted component:

$$shock^{c}_{prevwt} = \pi_i \times shock^{c}$$

Each approach yields a distinct composite index. For population weights, the index is calculated as:

$$CompositeIndex^{\text{popwt}} = \sum_{c} shock^{\text{c}}_{\text{popwt}},$$

And for prevalence weights, the index becomes:

$$CompositeIndex^{\text{prevwt}} = \sum_{c} shock^{\text{c}}_{\text{prevwt}},$$

3. Data description

The data used in this study originate from the FAO (2025) Data in Emergencies (DIEM) Information Hub, which implements rapid, nationally representative household surveys in crisis-affected contexts. In Nigeria, the sampling frame was constructed using recent national census and administrative population data to ensure coverage across geopolitical zones and livelihood systems. A stratified multi-stage sampling design was applied, with primary sampling

[1] *The shock prevalence weight π_c represents the proportion of households in the sample that reported experiencing at least one shock in category c. Formally, it is computed as:*

$$\pi_c = \frac{1}{N}\sum_{i=1}^{N} \mathbf{1}(shock^{c}_{i} = 1)$$

where N is the total number of households, and $\mathbf{1}(\cdot)$ is an indicator function equal to 1 if the household experienced a shock in category c, and 0 otherwise. This weighting adjusts each shock category by its relative frequency in the population, emphasizing common shocks and down-weighting rare or idiosyncratic ones.

units selected proportionally to population size and households randomly selected within clusters. Sampling weights were constructed to restore national representativeness.

Data were collected through structured household interviews using standardized questionnaires administered by trained enumerators. Respondents were asked to report whether their household experienced specific shocks within the previous 12 months, including economic, climatic, agricultural, health, and conflict-related events. The 12-month recall period was chosen to balance recall accuracy with the need to capture seasonal and systemic events.

Quality control measures included enumerator training, pre-testing of survey instruments, real-time monitoring of data consistency, and automated checks for logical inconsistencies during data entry. Post-collection cleaning procedures included range checks, duplicate removal, and verification of extreme values. Survey weights were applied in descriptive analyses to maintain representativeness.

Designed to provide timely, granular insights into the socioeconomic and food security conditions of rural and vulnerable populations, this dataset integrates modules on demographics, livelihoods, agriculture, food security, shocks, coping mechanisms, and humanitarian assistance.

It covers 12,595 households, each of which is geographically identified through standard administrative units reflecting Nigeria's subnational administrative structure. A central theme within the dataset is the exposure to shocks, which are recorded across multiple dimensions, such as economic, agricultural, natural, and conflict-related disruptions. Each is encoded as a binary variable indicating whether a household experienced the event. These data provide a foundation for constructing composite shock indexes and for exploring the interaction between shocks and food security outcomes.

Food security itself is measured using several internationally recognized metrics. The Food Consumption Score (FCS) provides a total score and disaggregated scores across food groups. The FCS is complemented by the Household Dietary Diversity Score (HDDS) and the Reduced Coping Strategy Index (rCSI). Moreover, the Food Insecurity Experience Scale (FIES) adds a subjective yet behaviorally grounded dimension, measuring direct experiences.

Another strength of the dataset lies in its detailed accounting of livelihood activities, covering agriculture, livestock, and fishing. Agricultural data include cropping systems, irrigation, seed sourcing, harvest volumes, and production difficulties. Livestock-related variables track herd size, production shocks, and marketing challenges, with distinctions drawn between increases due to acquisition and decreases due to distress sales or health issues. Similarly, fisheries data report the mode of fishing, production issues, and barriers to input access. These livelihood modules allow for in-depth analysis of production shocks and supply-side constraints at the household level.

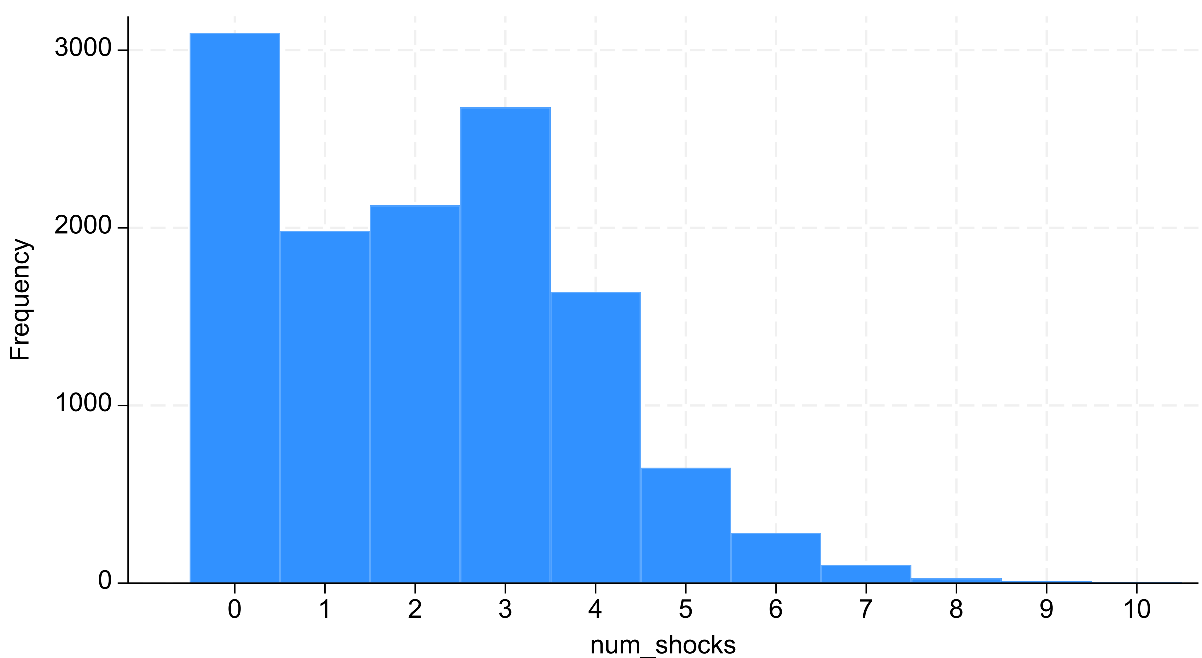
Coping strategies in the face of adversity are represented through a set of binary indicators. These variables not only reflect household-level adaptive behavior but also serve as proxies for resilience and socioeconomic buffering capacity. Importantly, these variables are used in downstream econometric models to predict vulnerability, enabling endogenous modeling of shock susceptibility.

In addition to exposure and response, the dataset also documents household needs and external assistance. This includes perceived needs and aid received from various actors such as the WFP, FAO, government, and others. These variables are crucial for evaluating the targeting efficiency and coverage of emergency programs and for identifying gaps in assistance delivery.

Distribution of Households by Number of Shocks

Figure 1 reveals the distribution of self-reported shocks, showing a right-skewed pattern. Most households report 0–2 shocks, but a notable tail of the distribution represents households experiencing five or more. These data reflect experienced shock incidence—not exposure in the environmental or macroeconomic sense.

Figure 1: Distribution of households by number of shocks



The distribution is skewed to the right, indicating that while many households experienced few to no shocks, a non-negligible portion encountered multiple simultaneous or sequential disruptions. The modal value—the most frequent number of shocks (num_shocks)—is zero, with over 3,000 households reporting no shock exposure during the survey period. This suggests that a substantial subset of the population remains relatively insulated, potentially due to geographic location, livelihood type, or access to buffers such as savings or social networks.

However, as the distribution progresses, there is a gradual decline in frequency for households reporting one, two, or three shocks, followed by an even steeper decline beyond four shocks. This tail represents a particularly vulnerable group: those households exposed to five or more shocks, which, although less common, likely face compounded disadvantages. This clustering of shocks may include combinations of economic hardship, climatic stressors, health-related events, and conflict—all of which can interact to deepen poverty traps and limit recovery capacity. According to Barrett and Carter (2013), repeated or simultaneous shocks can lead to a "poverty trap", wherein households cross critical asset thresholds that hinder future livelihood rebuilding, leading to chronic food insecurity and long-term vulnerability.

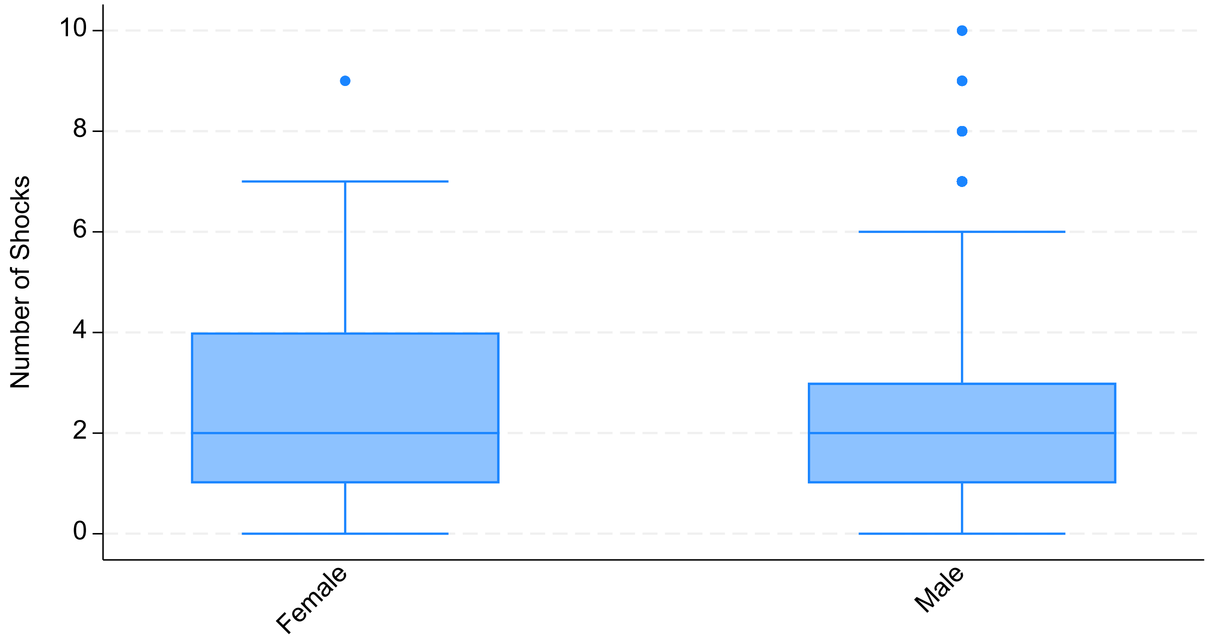
The occurrence of households experiencing as many as seven or more shocks—albeit infrequent—raises questions about resilience thresholds and adaptive capacity. These extreme cases are critical for humanitarian response planning, as they often signal systemic failure in social safety nets or environmental resilience. Studies by Heltberg et al. (2009) and the FAO (2018) emphasize that exposure to multiple shocks not only increases immediate hardship but also compromises future income generation, productivity, and child welfare, especially in agriculture-dependent households.

Another noteworthy observation is the frequency of households experiencing two to four shocks, which together comprise a substantial portion of the population. This mid-range of the distribution suggests that vulnerability is not confined to the extremes; rather, a large segment of the population is under continuous stress. These households may not qualify for emergency assistance, yet are persistently at risk of sliding deeper into food insecurity and asset depletion. As noted by Carter et al. (2007), this group often faces "latent vulnerability," where coping strategies become increasingly erosive—such as selling productive assets or reducing expenditures on health and education.

Number of Shocks by Household Gender

Figure 2 offers valuable insight into the gender-differentiated experience of shock exposure among Nigerian households. It visually compares the distribution of shocks experienced by women-headed households and male-headed households, capturing key statistical features such as medians, interquartile ranges, and outliers. From Figure 2, it is evident that female-headed households tend to experience a greater number of shocks than their male-headed counterparts. The median number of shocks for women-headed households is around 2, slightly higher than that male-headed households. Moreover, the interquartile range (IQR)—which captures the middle 50 percent of values—is wider for women-headed households, extending from approximately 1 to 4 shocks. In contrast, male-headed households have a narrower IQR, suggesting a more concentrated experience of shocks with less variability.

Figure 2: Number of shocks by household gender



The presence of higher whiskers and more extreme outliers in the women-headed group further suggests that women-headed households are more likely to face not just more frequent but also more compound or severe shocks. These may include economic stress (such as rising food prices), climate-related hazards, or social vulnerabilities such as illness or loss of employment. This pattern reflects longstanding evidence in development literature that women-headed households are often structurally more vulnerable, due in part to limited access to land, credit, and social protection systems (Quisumbing et al., 2015).

Conversely, male-headed households, while still significantly affected by shocks, tend to report a slightly lower average number, with fewer extreme cases. This might reflect not just exposure but differences in reporting behavior, social roles, or gendered divisions in asset ownership and decision-making authority. The narrower spread could also reflect better access to informal networks or livelihood diversification options that buffer male-headed households from multiple overlapping shocks.

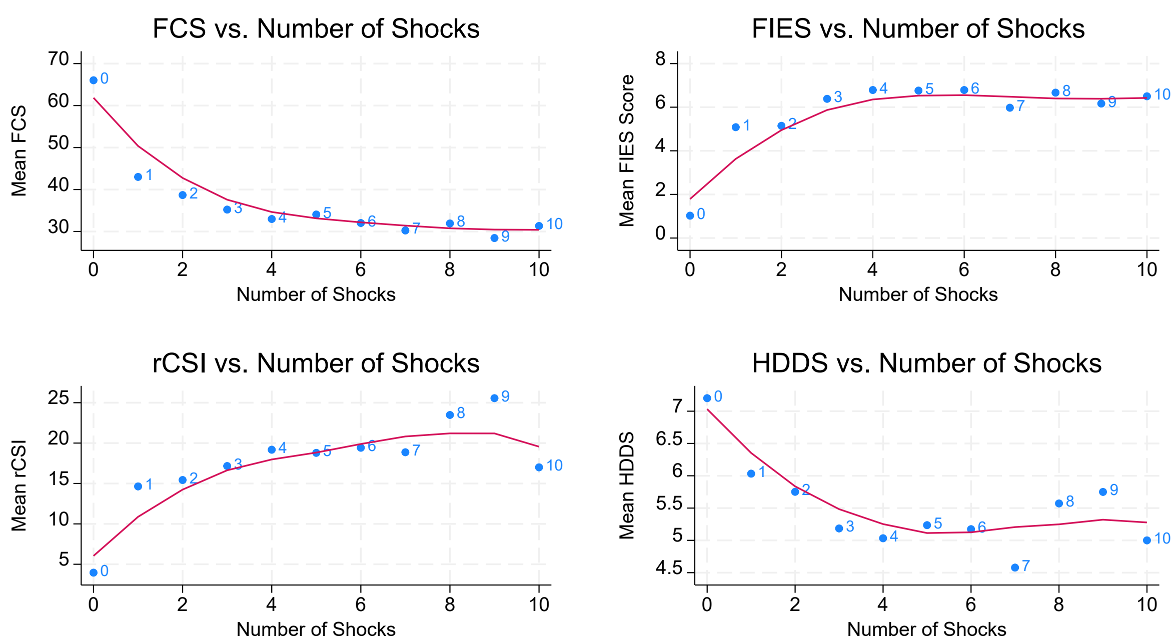
The implications of these differences are profound. Exposure to multiple shocks is closely linked with reduced resilience, as households must draw upon coping strategies that can erode long-term well-being—such as selling productive assets, withdrawing children from school, or reducing food consumption. When these behaviors are more common among women-headed households, the cycle of vulnerability is perpetuated across generations, particularly affecting children’s health and education outcomes (FAO, 2018).

Moreover, the gender disparities illustrated in this figure underscore the importance of mainstreaming gender in risk reduction and resilience programming. Simply put, gender-neutral interventions may not be sufficient to protect or empower those most at risk. There is a growing consensus in policy and academic literature that gender-sensitive targeting, including tailored cash transfers, agricultural support for women farmers, and enhanced access to financial services, can play a critical role in narrowing these vulnerability gaps (World Bank, 2022).

Food security outcomes vs. number of shocks

The panel (Figure 3) of scatter plots with smoothed trend lines presents a compelling picture of how cumulative exposure to shocks influences household food security in Nigeria. Each graph plots the average value of a key food security outcome—FCS, FIES, rCSI, and HDDS—against the number of shocks reported by a household. The results point toward a clear pattern: as the burden of shocks increases, food security deteriorates.

Figure 3: Food security outcomes versus number of shocks



The top-left graph shows a pronounced decline in the average FCS as the number of shocks increases. FCS, a composite indicator of dietary diversity, food frequency, and relative nutritional importance, sharply drops from over 60 for households with no shocks to around 30 for those facing ten shocks. This finding aligns with global literature indicating that multiple shocks erode household food access and diet quality (Maxwell et al., 2013; WFP, 2008).

FIES scores (top-right) increase as shock exposure rises, plateauing around a score of 6–7 after four or more shocks. A higher FIES score denotes more severe experiences of food insecurity, such as worrying about food or skipping meals. This pattern confirms that shocks—particularly when accumulated—undermine food security both in perception and behavior, as found in similar analyses across sub-Saharan Africa (FAO, 2021).

The rCSI also increases with the number of shocks (bottom-left graph), rising steeply between 0 and 5 shocks. The rCSI measures the frequency of coping behaviors like reducing meal portions or borrowing food. The upward trend indicates that households are increasingly resorting to stress, crisis, and emergency coping mechanisms as their shock burden grows. This mirrors findings from Ethiopia and South Sudan, where similar trajectories were observed in response to climate and market shocks (WFP, 2020; Headey & Ruel, 2020).

The HDDS, shown in the bottom-right graph, declines steadily from about 6.5 to below 5 as shocks increase. The HDDS captures the number of different food groups consumed in a household and is strongly associated with caloric adequacy and micronutrient intake. The observed pattern suggests that households reduce dietary diversity under stress, likely substituting nutritious but expensive items with cheaper, energy-dense foods. This is consistent with evidence from Nigeria and Kenya, where droughts and food price shocks led to simplification of household diets (FEWS NET, 2018).

In summary, the evidence points to the peril of cumulative shocks. By investing in predictive, multi-dimensional tools like the MSI, and aligning them with responsive programming, policymakers and humanitarian actors can not only mitigate damage but strengthen household resilience over time.

Idiosyncratic versus systemic shocks

In economic and social policy contexts, the terms idiosyncratic and systemic shocks describe two distinct types of disruptions, each with different origins, magnitudes, and implications for risk management and response. While these concepts are foundational in economics and finance, they are increasingly critical in the design of humanitarian responses and resilience-building interventions, particularly in low-income and fragile settings where systems are vulnerable and resources are constrained.

Idiosyncratic shocks affect individuals, households, or specific entities without influencing broader systems. These shocks are often unpredictable and include events such as illness, death of a household earner, or loss of livestock. Because they are isolated, they generally do not threaten entire communities or systems. In resilience planning, idiosyncratic shocks are typically addressed through mechanisms like social protection programs, micro-insurance, and targeted assistance. These instruments help individuals and households recover without placing a heavy burden on wider institutions.

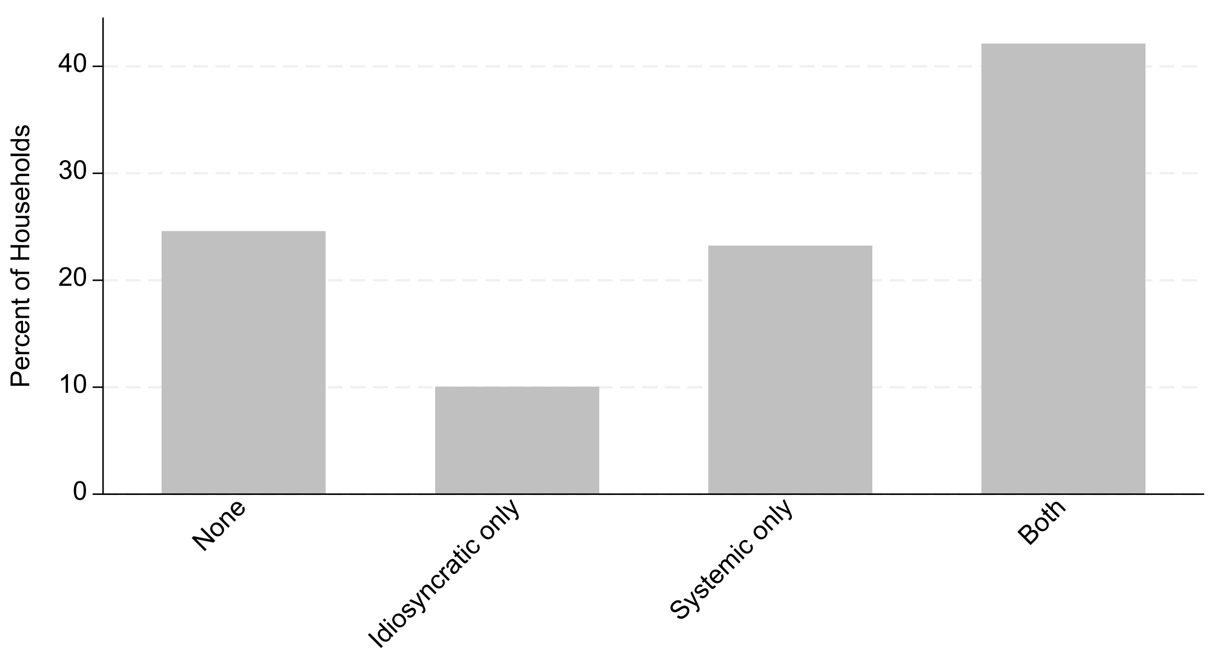
Conversely, systemic shocks—such as pandemics, droughts, economic recessions, or political crises—have far-reaching effects across entire populations, sectors, and regions. These shocks challenge institutional capacity, disrupt supply chains, and can trigger widespread humanitarian crises. For example, the COVID-19 pandemic was a systemic shock that strained health systems, halted education, and exacerbated food insecurity globally. In these contexts, the scale and complexity of the shock necessitate large-scale, coordinated interventions, often involving governments, international agencies, and humanitarian actors.

Understanding the distinction between these two types of shocks is crucial for effective humanitarian planning and resilience building. When interventions fail to differentiate between idiosyncratic and systemic shocks, responses can be mismatched in both scale and design. For instance, treating a systemic food crisis as a series of household-level food insecurities may result in under-resourced or fragmented responses. On the other hand, overreacting to localized or idiosyncratic events with system-wide policies can be inefficient and financially unsustainable.

Moreover, the line between idiosyncratic and systemic shocks is not always fixed. As Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015) note, in highly connected systems, even small idiosyncratic shocks can evolve into systemic crises. This is especially relevant in fragile contexts where institutions are weak and vulnerabilities are widespread. For example, a localized conflict or disease outbreak can escalate into a systemic crisis if governance, healthcare, or food systems are already under stress.

Figure 4 offers critical insight into the landscape of household vulnerability in Nigeria by categorizing shock exposure into four groups: no shock, idiosyncratic only, systemic only, and both. The data reveal a striking pattern of compounded risk, with implications for both emergency response and long-term policy planning.

Figure 4: Distribution of households by shock type



A significant proportion—approximately 42 percent—of households experienced both idiosyncratic and systemic shocks. This finding underscores the prevalence of overlapping vulnerabilities among households. Idiosyncratic shocks such as job loss, illness, or interpersonal violence are often unexpected and deeply personal in their impact. When compounded with systemic shocks like droughts, price inflation, or flooding, the resilience capacity of households may be severely stretched. The prominence of this dual-exposure group highlights the necessity for integrated resilience-building strategies that can address both individual- and community-level risks simultaneously.

Meanwhile, about 24 percent of households experienced only systemic shocks. This is consistent with the nature of systemic events, which tend to affect entire regions or markets. The widespread reach of such shocks makes them particularly disruptive, especially for agrarian or informal-sector populations whose livelihoods are tightly linked to climate patterns or market conditions.

By contrast, only 10 percent of households reported experiencing idiosyncratic shocks in isolation. This relatively smaller group reinforces the idea that these shocks are unevenly distributed, often affecting households based on health status, employment volatility, or exposure to conflict and crime. While less widespread, these shocks can be equally devastating at the individual level and demand responsive, targeted interventions.

Overall, Figure 4 presents a clear message: household vulnerability in Nigeria is multidimensional and often compounded. The high share of households facing both systemic and idiosyncratic threats suggests that single-layered policy solutions are insufficient. Rather, policy responses must be layered and adaptive—combining universal mechanisms (e.g., early warning systems, input subsidies) with targeted social protection (e.g., cash transfers, community-based insurance) to address the full spectrum of household shock exposure.

4. Application

4.1. To weight or not to weight

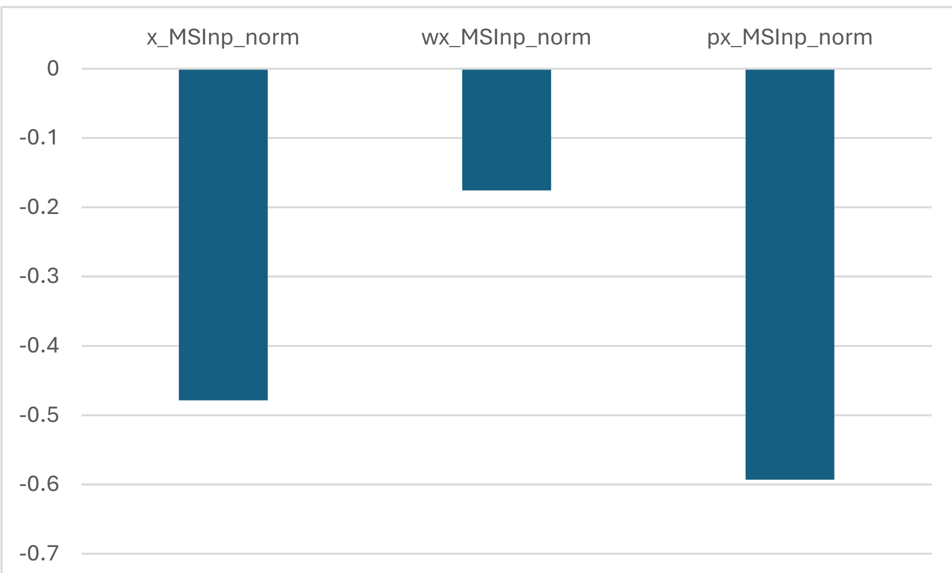
In settings marked by chronic food insecurity and frequent disruptions—from economic volatility and climate extremes to pandemics and conflict—accurately assessing household vulnerability is both urgent and complex. Standard approaches often rely on parametric models, which, while useful, require strong assumptions about functional form and error structure that may not hold in real-world, multi-shock environments. In contrast, non-parametric indexes provide a more flexible and assumption-light alternative, enabling analysts to aggregate diverse shock experiences into composite indicators of exposure.

This section explores and compares three non-parametric indexes constructed from a curated set of shocks empirically linked to reductions in FCS. These indexes—unweighted, weighted by household, and weighted by national shock prevalence—aim to capture the cumulative burden of shocks at the household level. The core objective is to assess which index offers the most reliable, interpretable signal of food security risk without resorting to regression-based modeling, making them suitable for rapid diagnostics, operational dashboards, and real-time targeting frameworks.

Correlation with FCS

A Pearson correlation (see Figure 5) was used to assess the linear association between each index and FCS, where negative values are expected—in other words, when there is an increase in shocks, we expect food security to be lower. The prevalence-weighted index (px_MSInp_norm) shows the strongest negative correlation, suggesting it best reflects how increasing shock burden erodes household food security. This is theoretically consistent with the idea that more common shocks, such as drought or price inflation, may have more systematic and widespread effects, and thus should weigh more heavily in composite measures (Maxwell et al., 2013).

Figure 5: Correlation with FCS



In contrast, the population-weighted index (wx_MSInp_norm) has the weakest correlation, indicating that adjusting shocks by survey weights—typically used for population representation—may dilute meaningful differences between households. This implies that while weights help describe *populations*, they may not always improve *individual-level diagnostics*.

Group mean differences by vulnerability

To test discriminative power, households were grouped using an FCS threshold of 21—a score below 21 indicates severe food insecurity, per WFP standards. We then calculated the average index score for each group (Table 1).

Table 1: Index means by FCS group

Index	Mean (FCS ≥ 21)	Mean (FCS < 21)	Interpretation
Unweighted index	0.2051	0.2632	Moderate separation
Weighted index (Population)	0.0585	0.0577	No separation
Weighted index (Prevalence)	0.2322	0.4379	Strong separation

The large gap between food-secure and food-insecure households in the px_MSInp_norm scores reinforces its discriminatory validity. Households with low FCS had substantially higher exposure to prevalent shocks. This suggests that this index captures meaningful variation in vulnerability.

By contrast, the negligible difference in the population-weighted index (wx_MSInp_norm) implies it lacks sensitivity to household-level food insecurity. This again suggests that population representativeness (weights) may mask individual risk factors, particularly when vulnerability is spatially clustered or heterogeneously distributed (Hoddinott & Quisumbing, 2003).

Quartile gradient analysis

To assess stratification power, households were divided into quartiles based on each index. Mean FCS scores were then examined across these quartiles (Table 2).

Table 2: FCS mean by index quartile

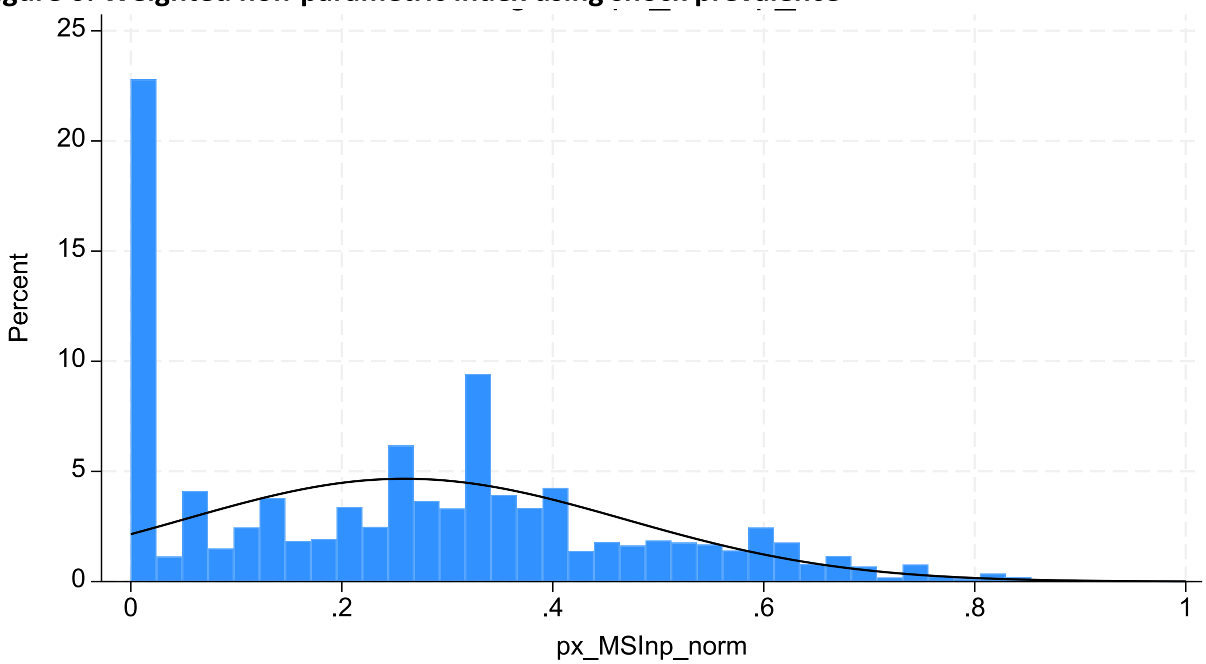
Quartile	Unweighted index	Weighted index (Population)	Weighted index (Prevalence)
Q1 (Low)	57.05	65.00	66.63
Q2	38.68	35.03	45.30
Q3	35.22	37.34	36.01
Q4 (High)	33.01	39.01	28.54

The px_MSInp_norm index again performs best, showing a smooth, consistent decline in food security from Q1 (least shocks) to Q4 (most shocks). This pattern not only confirms that the index is ordered meaningfully but also shows it is a useful proxy for progressive vulnerability. The x_MSInp_norm shows a weaker but still monotonic trend. The wx_MSInp_norm shows a non-monotonic trend with erratic jumps, undermining its value for stratification. This ability to stratify households into distinct vulnerability bands is vital for program design, especially when budget constraints require targeting only the most at-risk households (FAO, 2008).

Distributional pattern

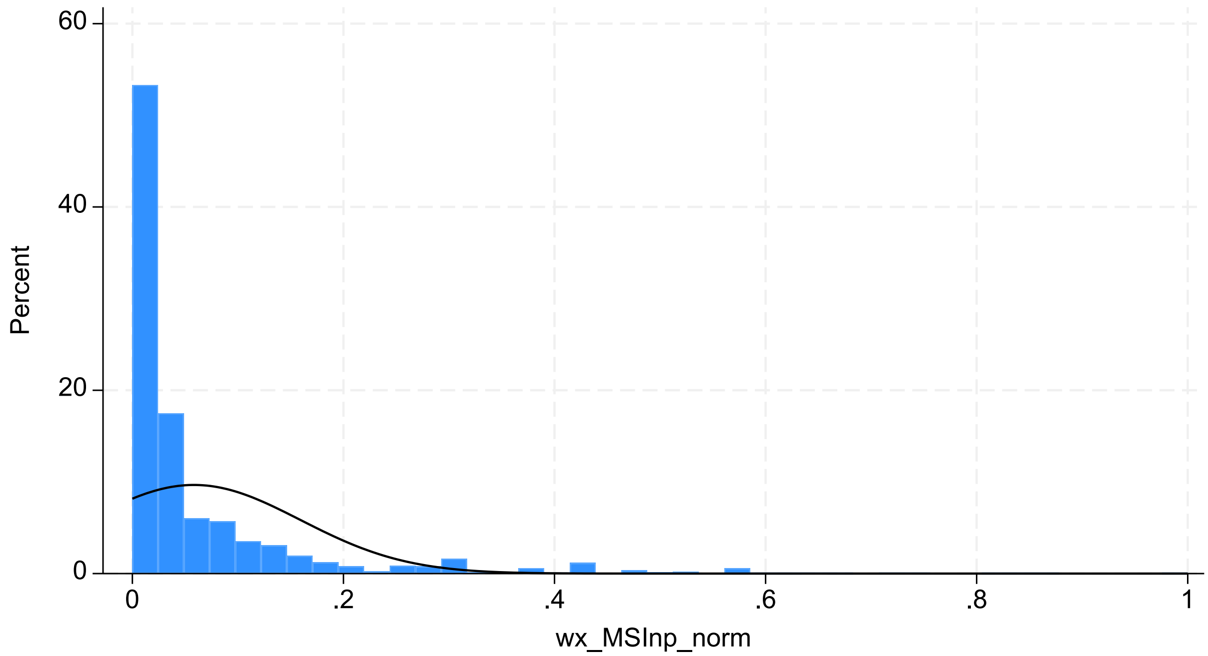
Among the three, the prevalence-weighted index (Figure 6) stands out for its rich distributional properties. Its values span the entire normalized range from 0 to 1, capturing a wide spectrum of household experiences. While some clustering is visible at the lower end, consistent with the fact that many households report limited or no shocks, the index maintains meaningful variation across the rest of the scale. This balance between density and dispersion is particularly valuable for applied work, as it allows analysts and practitioners to both detect severely-effected households and observe subtler gradations in vulnerability. It is especially well-suited for dashboard visualizations, geospatial mapping, and other operational tools that require fine-grained differentiation across units.

Figure 6: Weighted non-parametric index using shock prevalence



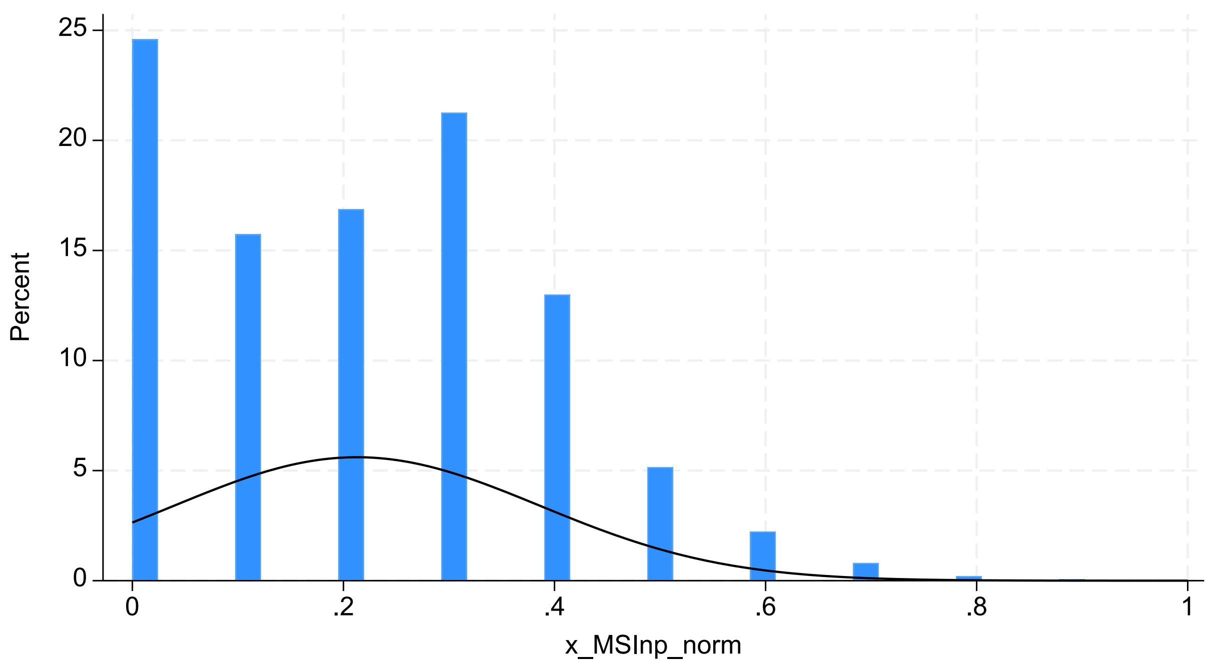
In contrast, the population-weighted index (Figure 7) exhibits a narrow and compressed distribution, with a substantial proportion of values tightly clustered near zero. This suggests that it may underrepresent households with moderate exposure and, in turn, reduce the index's analytical sensitivity. While population weights may serve useful design purposes in survey estimation, applying them in this context appears to mute the index's ability to differentiate among levels of shock severity. Such compression reduces the statistical power of downstream analyses and limits its applicability for nuanced targeting or real-time monitoring.

Figure 7: Weighted non-parametric index using population sampling



Finally, the unweighted index (Figure 8) provides a middle ground in terms of spread and shape. Though it captures more variation than the population-weighted index, it still lacks the tailored adjustment for shock prevalence that gives the prevalence-weighted index its empirical nuance.

Figure 8: Unweighted non-parametric index



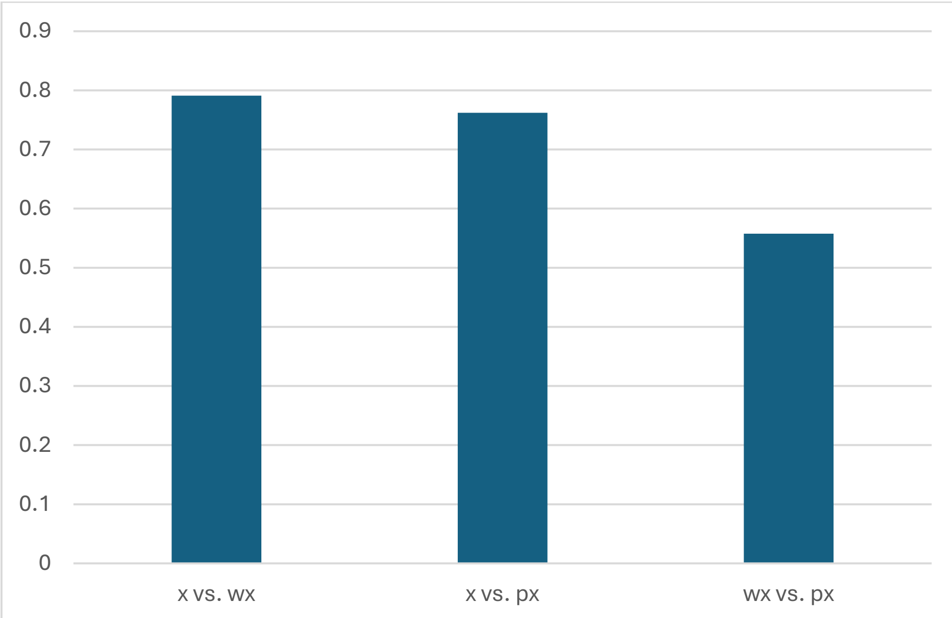
Taken together, the distributional evidence suggests that px_MSInp_norm offers the most operationally useful profile of the three indexes. Its broader spread and better balance between concentration and variation make it more informative for decision-making, particularly in contexts where prioritization and classification of household vulnerability are key.

Rank correlation between indexes

Rank correlation assesses the degree to which two indexes agree in the way they order or rank households according to shock exposure. Unlike standard correlation, which measures linear association between raw values, rank correlation focuses on ordinal relationships—that is, whether households deemed more exposed by one index are also considered more exposed by another. This is particularly useful when comparing indexes that differ in scale, weighting scheme, or distribution. A high rank correlation (close to 1) indicates strong agreement in relative household rankings, suggesting that the indexes are broadly substitutable for targeting or classification purposes. Conversely, lower rank correlations reveal divergence in how indexes prioritize vulnerability, highlighting potential trade-offs in index selection depending on analytical or operational objectives. In this study, rank correlations help clarify whether different weighting strategies (e.g., prevalence-based vs. unweighted) lead to consistent household prioritization—a critical consideration for program eligibility, resource allocation, or real-time dashboard reporting.

Although the unweighted and prevalence-weighted indexes are moderately correlated (0.76), the lower correlation between wx and px (0.56) suggests that each ranks households differently (Figure 9). This is important because it indicates that px_MSInp_norm introduces non-redundant insights, which are especially valuable for better targeting or prioritizing of regions.

Figure 9: Spearman rank correlation



Note: x refers to unweighted index; wx, to weighted (population); and px, to weighted (prevalence).

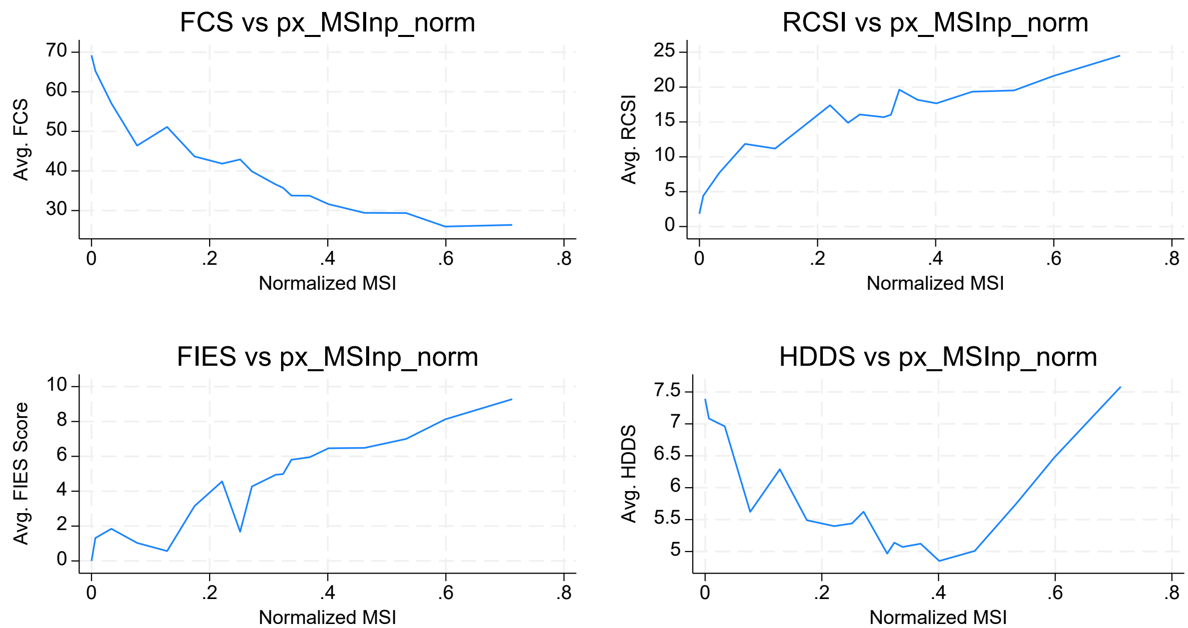
Thus, px_MSInp_norm provides a more differentiated and consistent ordering of households based on their cumulative exposure to shocks. This rank consistency means that the index not only identifies broad trends but it also helps distinguish with greater precision who is relatively more or less vulnerable within a population. Operationally, this index is invaluable for ranking-based decisions, such as prioritizing households for cash transfers, tiered humanitarian assistance, or graduated program entry points. When resources are limited and interventions must be sequenced or scaled, having an index that offers both predictive accuracy and fine-grained household differentiation allows policymakers and implementers to act with both fairness and efficiency. The added value of px_MSInp_norm lies not just in how well it tracks outcomes, but in how effectively it informs strategic targeting and resource allocation under pressure.

4.2. Food security outcomes and MSI

Figure 10 presents a binned average analysis that maps how increasing exposure to shocks—measured using a non-parametric MSI, relates to four core food security indicators:

- FCS: Food Consumption Score
- rCSI: Reduced Coping Strategy Index
- FIES: Food Insecurity Experience Scale
- HDDS: Household Dietary Diversity Score

Figure 10: Food security outcomes vs. non-parametric MSI



Each plot reflects averages within 20 quantile bins of px_MSInp_norm, offering a smoothed but empirically grounded view of trends across the population. The x-axis is the normalized shock index (from low to high shock burden), and the y-axis represents the average value of the corresponding outcome.

Food Consumption Score falls consistently as shock exposure increases. This panel shows a clear and steep downward trend, indicating a strong negative relationship between cumulative household shock exposure and food consumption adequacy. Households in the lowest deciles of the MSI report FCS scores above 60 (indicating acceptable food security), while those in the highest shock exposure brackets fall below 30—borderline or poor consumption levels.

This pattern is both empirically intuitive and policy relevant. FCS is a composite measure of dietary diversity, frequency, and nutrient density over the past week. Households facing multiple, frequent, or prevalent shocks likely experience disruptions in market access, income, or asset buffers—all of which directly impair food purchasing and consumption (WFP, 2009).

Use of negative coping strategies increases with higher shock burden. The upward slope here demonstrates a positive and nonlinear association between MSI and coping strategies. The rCSI aggregates behaviors such as reducing meal sizes, skipping meals, or eating less preferred foods. It reflects short-term adaptations to food stress.

At low levels of shock exposure, the average rCSI is around 5–10; by the upper end of the shock index, it climbs to over 20. This strongly suggests that households progressively exhaust less severe coping options and engage in more desperate measures as shocks accumulate.

Food insecurity experience worsens with increased shock exposure. The FIES is a globally standardized measure of perceived food insecurity, ranging from worry about food to actual hunger experiences. Its steady increase in relation to px_MSInp_norm demonstrates a psychosocial as well as physical impact of shocks. Interestingly, the trend is highly linear, suggesting that subjective food insecurity rises proportionally with shock exposure. This concordance across subjective and objective indicators adds robustness to the MSI's validity.

Dietary diversity declines initially, but rebounds at high shock levels. The Household Dietary Diversity Score (HDDS) is expected to decrease with shocks, and it does to a point. Initially, HDDS falls from about 7 to around 5 as MSI increases. However, a curious uptick appears in the highest MSI bins. This may reflect one of two phenomena:

- Programmatic targeting: Households with high MSI scores may be more likely to receive food aid or participate in nutrition programs, temporarily boosting diversity.
- Measurement artifact: In the upper tail of MSI, fewer households may create statistical noise or sampling bias.

Nevertheless, the initial downward trend supports MSI's expected relationship with reduced dietary variety, an early warning sign of deteriorating food access and nutrition (FAO, 2008). While the relationship is less monotonic than FCS, HDDS still declines with higher shock burden, confirming the MSI's sensitivity to nutrition-relevant shocks.

These trends validate the index as a composite vulnerability metric, capturing not only exposure to adverse events but also their downstream consequences across behavioral, nutritional, and experiential dimensions.

The prevalence-weighted MSI emerges as a practical and reliable tool for identifying households facing heightened food insecurity risks. Its consistent and interpretable relationship with multiple food security outcomes—ranging from consumption adequacy to coping behavior and subjective experience—demonstrates its value not only as an analytical construct but as an operational instrument. In the context of real-world humanitarian response and policy targeting, this index can be readily integrated into real-time monitoring systems to flag vulnerable populations before crises escalate. It offers a streamlined and evidence-based means of supporting early warning systems by providing timely insights into the cumulative burden of shocks.

Moreover, because the index is grounded in empirical prevalence patterns and reflects actual exposure experienced by households, it is particularly well-suited for geospatial targeting of interventions such as cash transfers or in-kind food assistance. Agencies and implementing partners can use it to inform geographic prioritization, identify pockets of vulnerability, or stratify populations based on severity. In programmatic settings, it can also serve as a threshold tool for determining eligibility for support, ensuring that scarce resources are allocated to those most at risk. As a composite indicator, it offers a scalable, low-complexity, and conceptually transparent metric that bridges the gap between data collection and decision-making.

4.3. Confirming the validity of the prevalence-weighted multi-shock index

A robust shock exposure index should not only summarize cumulative adversity but also behave predictably across multiple dimensions of household welfare. In the context of food security, this means that higher exposure to shocks should systematically correspond to worse outcomes—regardless of the specific indicator used. The prevalence-weighted multi-shock index (px_MSInp_norm) was designed with this principle in mind, aiming to capture the additive burden of shocks in a way that is both empirically grounded and programmatically useful.

To assess the index's validity, we regressed four distinct food security outcome variables—FCA, rCSI, FIES, and HDDS—on px_MSInp_norm, while controlling for key covariates including household need status, gender, education level, and second-level administrative unit. These outcomes capture a wide range of food-related experiences, from dietary diversity to behavioral coping and self-reported hunger.

Across all four outcomes and under four model specifications (linear, log-linear, quadratic, and log-quadratic), the direction of the relationship between px_MSInp_norm and food security outcomes was consistent with theoretical expectations (Table 3). Specifically, increases in the shock index are associated with lower FCS and HDDS scores, and higher rCSI and FIES scores. This negative association with dietary quality and adequacy, and positive association with food insecurity and coping burden, confirms that the index meaningfully captures household vulnerability in the food security domain.

Table 3: Regression of food security outcomes on MSI

Model	Outcome	Observations	R^2	AdjR^2	Coefficient	p-value
Linear	fcs	11878	0.40	0.40	-60.94	0
Log-linear	fcs	11878	0.45	0.44	-9.49	0
Quadratic	fcs	11878	0.44	0.44	-120.54	0
Log-quadratic	fcs	11878	0.45	0.45	-14.97	0
Linear	rcsi	11878	0.35	0.35	29.31	0
Log-linear	rcsi	11878	0.38	0.37	4.44	0
Quadratic	rcsi	11878	0.37	0.36	50.09	0
Log-Quadratic	rcsi	11878	0.38	0.38	7.77	0
Linear	fies	6323	0.82	0.82	12.70	0
Log-linear	fies	6323	0.74	0.73	1.75	0
Quadratic	fies	6323	0.82	0.82	14.82	0
Log-Quadratic	fies	6323	0.81	0.81	5.45	0
Linear	hdds	8494	0.21	0.19	-4.69	0
Log-linear	hdds	8494	0.23	0.22	-0.56	0
Quadratic	hdds	8494	0.23	0.22	-11.61	0
Log-Quadratic	hdds	8494	0.23	0.22	-0.58	0

Importantly, the consistency of sign across all models and all outcomes reinforces both the face validity and construct validity of the index. It suggests that px_MSInp_norm is not merely statistically significant but also substantively aligned with how compounded shocks are expected to affect household well-being. This robustness across diverse outcomes and specifications reduces the likelihood that observed associations are model artifacts or driven by outliers. Rather, they reflect a stable underlying relationship between cumulative shock exposure and food security status.

The practical implications are considerable. Because px_MSInp_norm performs reliably across food security metrics, it can serve as a general-purpose tool for ranking households by vulnerability. This can be directly applied to targeting of cash transfers, identifying early warning thresholds, and segmenting populations for differentiated resilience programming. The stability of the index makes it suitable for both cross-sectional analyses and for repeated use in real-time monitoring systems or dashboard interfaces.

Moreover, its non-parametric construction avoids the rigid assumptions of regression-based weighting schemes, while still producing results that align with policy-relevant outcomes. This positions px_MSInp_norm as a credible and adaptable metric for operational use in diverse humanitarian and development settings.

In contexts marked by recurrent shocks and limited resources, decision-makers require indicators that are both analytically sound and logistically feasible. The demonstrated consistency of px_MSInp_norm across food security outcomes confirms its value as a reliable compass for navigating complex vulnerability landscapes.

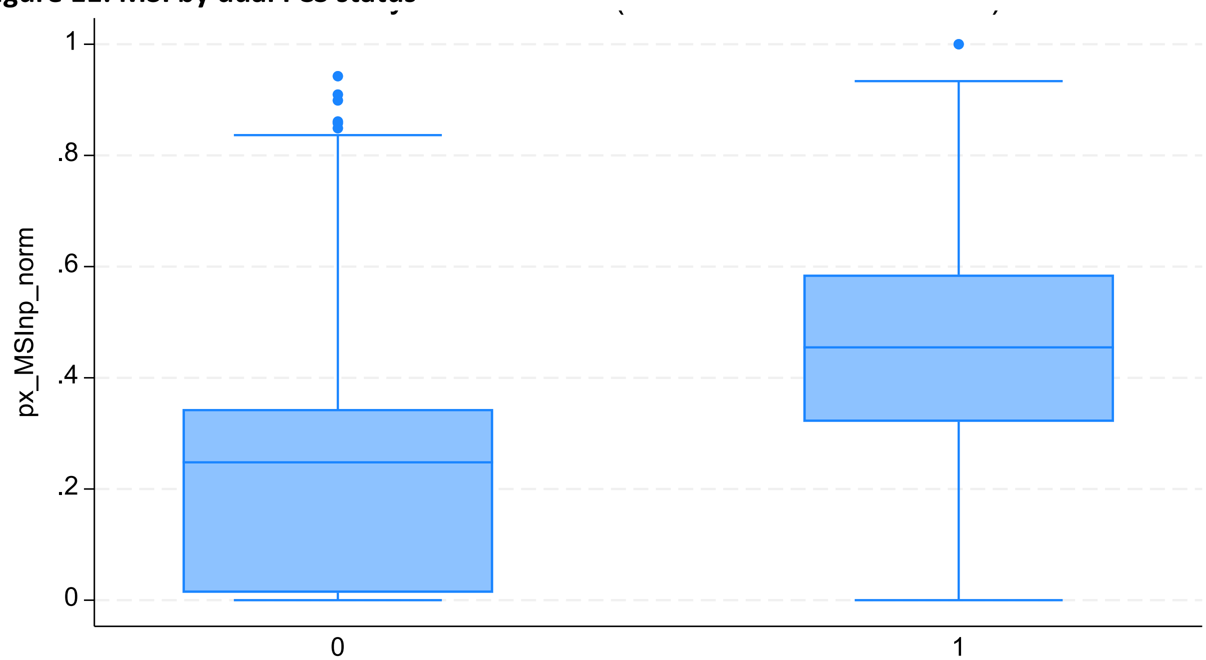
4.4. Benchmarking the multi-shock index (MSI) for resilience programming

In the context of rising systemic shocks—climate variability, economic crises, pandemics, and conflict—the ability to diagnose vulnerability in a nuanced, scalable, and empirically valid manner is more urgent than ever. The non-parametric multi-shock index (MSI) represents an important advancement in this direction. By capturing the cumulative burden of household-level exposure to multiple shocks—each weighted by its empirical prevalence—this index allows for a more accurate reflection of lived vulnerability. Yet, the practical utility of any index lies not only in its construction, but in how it is interpreted and operationalized. Benchmarking, or setting evidence-based thresholds, becomes essential in transforming px_MSInp_norm from a statistical construct into a decision-support tool for resilience building.

Benchmarking is vital because raw MSI values—ranging from 0 to 1—do not inherently convey what level of shock exposure constitutes "high risk," nor do they differentiate between urgent, moderate, or low-priority cases for policy and programming. To be meaningful, these values must be anchored in real-world outcomes. An impact-based benchmarking strategy is therefore appropriate, one that links MSI scores to observed levels of food insecurity—a primary manifestation of shock-induced vulnerability.

To this end, we employed the FCS, an internationally validated indicator that combines dietary diversity, food frequency, and nutritional value. By separating households into two categories—those deemed severely food insecure (FCS < 21) and those above this threshold—we found clear differences in MSI scores (Figure 11). Households below the FCS threshold consistently had significantly higher px_MSInp_norm scores, both in mean and distribution. This validates the use of the MSI as a proxy for actual welfare loss. The average MSI value among severely food-insecure households thus serves as an evidence-based threshold: any household with an MSI score above this point can be flagged as highly exposed to shocks and, by extension, as a candidate for targeted assistance or resilience-building interventions.

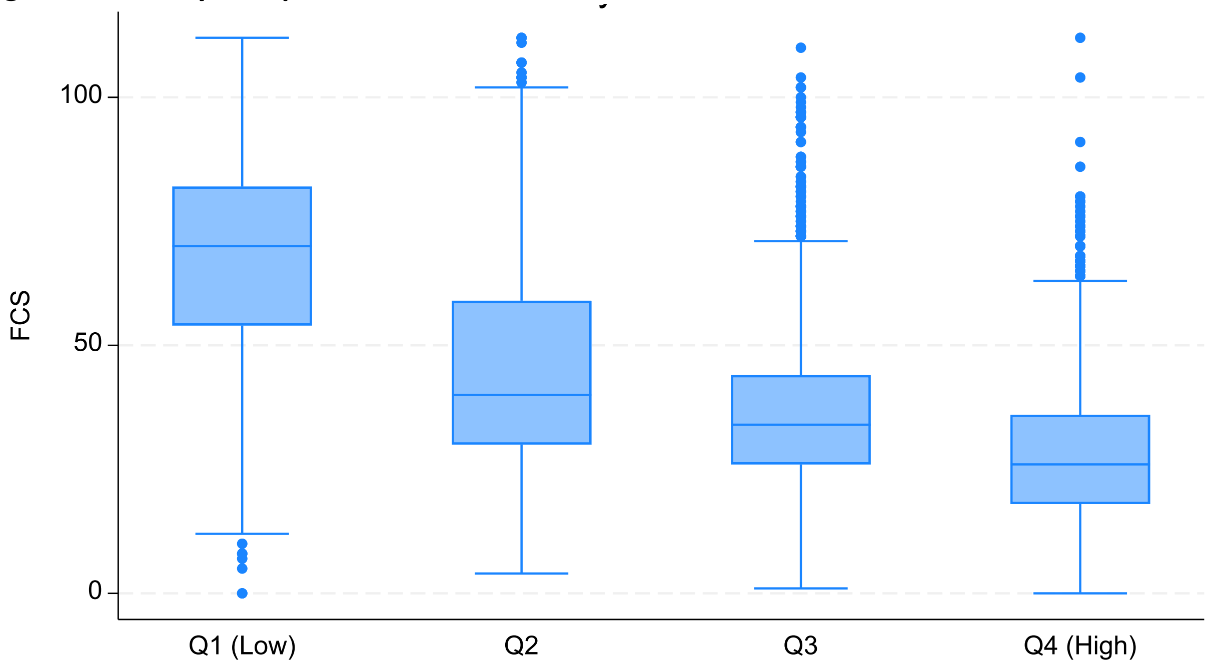
Figure 11: MSI by dual FCS status



Note: "0" means fcs<=21; "1" means fcs>21

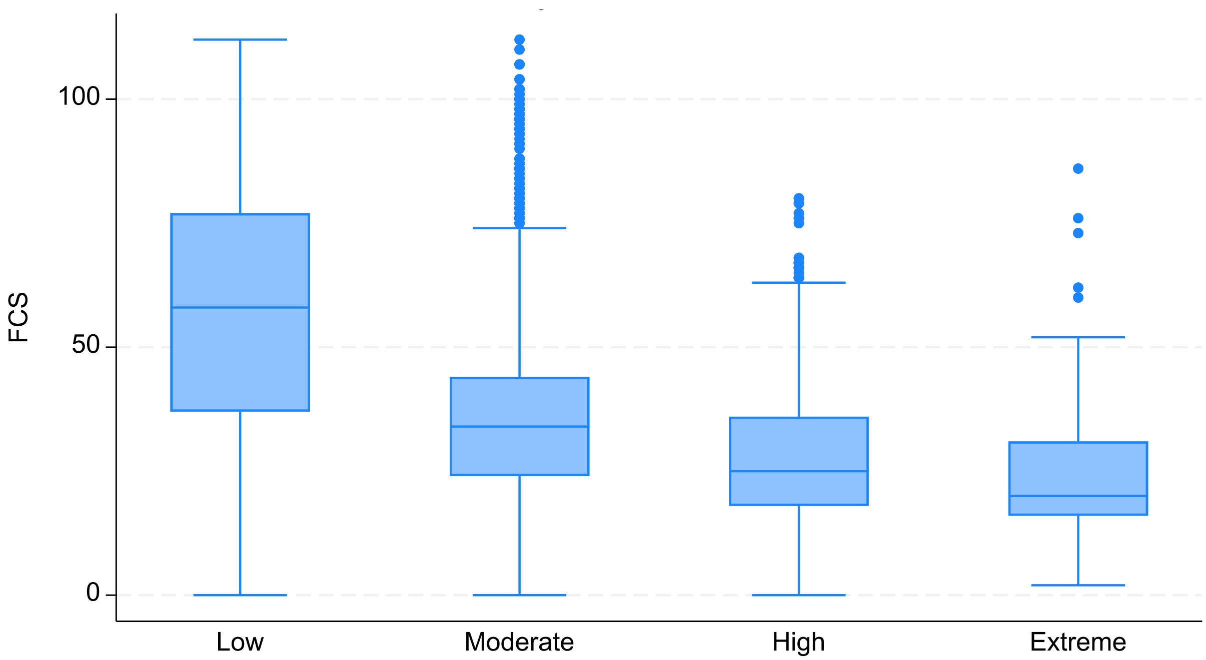
Beyond this outcome-based calibration, stratifying the population by quartiles of MSI exposure further refines our understanding. As we divide px_MSInp_norm into quartiles (Q1 to Q4), a strong monotonic relationship emerges (Figure 12): households in higher MSI quartiles consistently report lower FCS. The fourth quartile, which represents the top 25 percent of exposure, exhibits the poorest food security outcomes. This stratification method provides a relative vulnerability ladder and can be particularly useful for designing phased interventions, from early warning systems to tiered social protection responses.

Figure 12: MSI by FCS quartiles



To further support operational decisions, we introduced a four-tier risk categorization system using standardized MSI cutoffs (Figure 13). Households with MSI scores below 0.25 are classified as "low risk," those between 0.25 and 0.5 as "moderate risk," between 0.5 and 0.75 as "high risk," and those above 0.75 as "extreme risk." These tiers correspond with progressively worse food security outcomes and allow for differentiated programming. For instance, low-risk households may benefit from preventive resilience investments such as savings groups or access to microinsurance, while extreme-risk households may qualify for immediate cash transfers, food aid, or livelihood protection measures.

Figure 13: Resilience risk tier



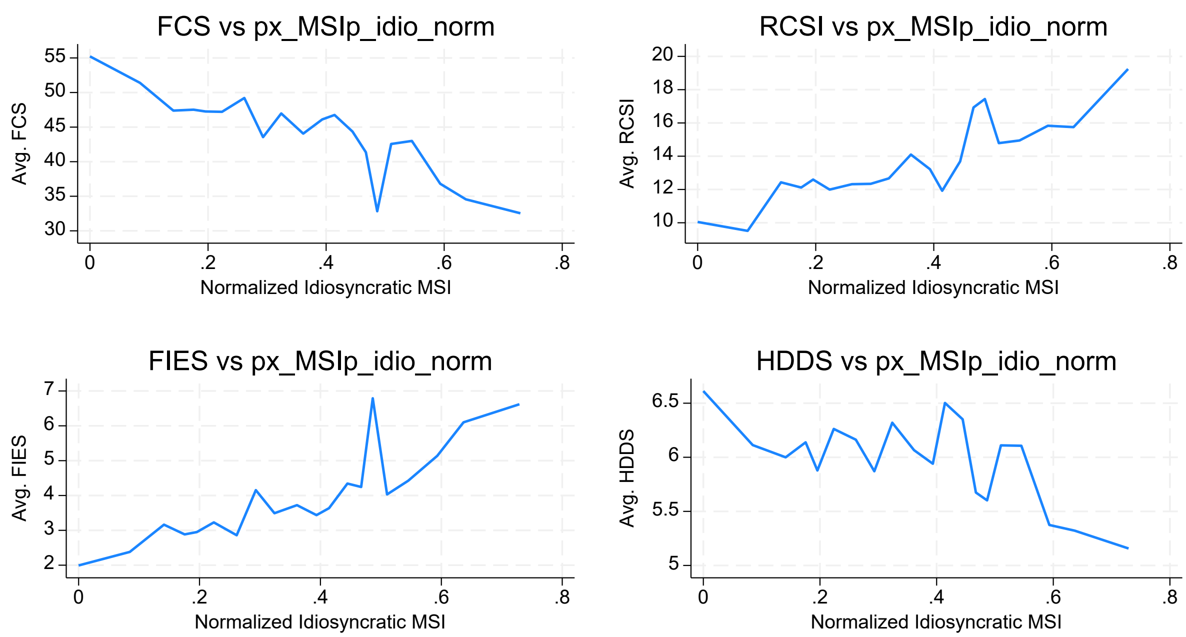
Such risk tiering is not only analytically sound but also programmatically useful. It aligns well with the adaptive social protection model promoted by the World Bank (2018), in which social protection systems expand vertically and horizontally in response to shocks. The use of benchmarks is not limited to static targeting. px_MSInp_norm, especially when tracked over time, can serve as a monitoring instrument. Rising scores could indicate deteriorating resilience, prompting early interventions before households fall into poverty traps. Conversely, declining scores could signal effective policy action or community adaptation, justifying resource reallocation.

In conclusion, benchmarking the multi-shock index is not merely a statistical exercise—it is a critical enabler of fair, timely, and effective action. By anchoring MSI scores to observed food insecurity and layering them into interpretable tiers, we translate complex exposure data into operational insight. This empowers governments, humanitarian actors, and development agencies to act with both precision and urgency, targeting those most in need while building systems capable of withstanding tomorrow's shocks.

4.5. Idiosyncratic and systemic shocks

Figures 14 and 15 offer rich visual evidence on how idiosyncratic shocks and systemic shocks are associated with food security outcomes in Nigeria. Figure 14 reveals the relationships between idiosyncratic shock exposure and household food security outcomes. Idiosyncratic shocks refer to household-specific events such as death, theft, illness, or intra-household crises.

Figure 14: Food security outcomes and Idiosyncratic MSI



The plot of FCS against px_MSIp_idio_norm shows a moderately declining trend. While the drop is not perfectly linear, the average FCS falls from above 55 in the lowest MSI quantiles to around 30 in the highest. This decline suggests that as households face more idiosyncratic shocks, their access to an adequate and diverse diet declines—though the relationship appears somewhat noisy, likely reflecting coping strategies or external supports buffering food consumption in some cases.

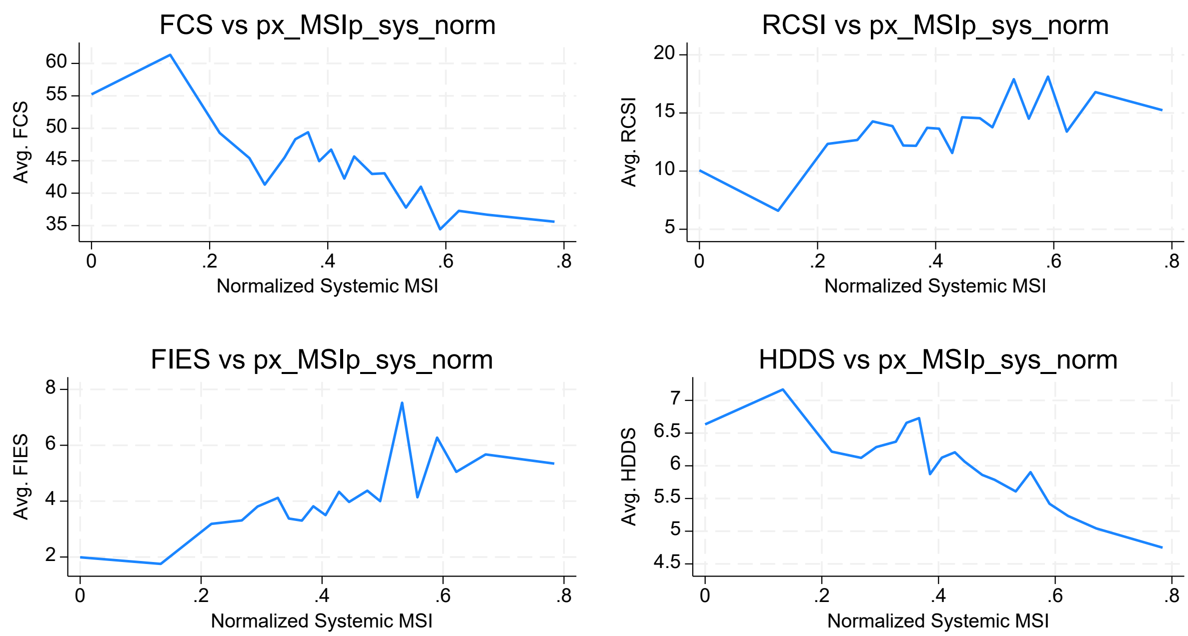
For rCSI, the association is more consistent and clearly positive. The rCSI rises from around 10 to nearly 20 as the idiosyncratic shock index increases. This pattern confirms that households experiencing more individualized shocks increasingly resort to negative coping mechanisms, such as reducing meal portions, borrowing food, or skipping meals. The steady climb reflects the strain on short-term resilience capacity among affected households.

The FIES similarly increases with the MSI, albeit more gradually. The trajectory reveals that food insecurity—measured by subjective experiences of anxiety, hunger, or deprivation—deepens as households encounter more shocks. The shape of the line suggests an accumulative effect, where a few shocks may not tip households into severe insecurity, but multiple shocks do.

In contrast, HDDS demonstrates a gradual decline, moving from an average of 6.5 to just above 5 as MSI increases. The relationship is not as steep as with the rCSI or FCS, but the downward trend confirms that dietary quality erodes under the pressure of repeated or intense personal shocks. However, the fluctuations indicate that households may prioritize dietary diversity (for example, by accessing less expensive but diverse foods) until constraints become too severe.

Figure 15 shows the effect of systemic shocks, which include community-wide or structural events such as droughts, floods, price spikes, or disease outbreaks. The pattern for FCS is more sharply defined here than in the idiosyncratic case. The average food consumption score begins around 60 and declines steadily to the mid-30s as systemic MSI increases. This stronger gradient suggests that system-wide shocks have a more immediate and uniform effect on food consumption, perhaps because they affect both food availability (markets, production) and purchasing power (prices, income loss) at scale.

Figure 15: Food security outcomes and systemic MSI



The relationship with rCSI is also positive, similar to the idiosyncratic plot. However, the increase levels off at high MSI values, possibly indicating that households eventually exhaust coping strategies or reach a behavioral ceiling. This flattening suggests that while systemic shocks provoke coping behaviors, their ability to escalate rCSI may be capped by practical limits on what households can do.

In the FIES plot, we again observe a steady increase in food insecurity as the systemic MSI rises. The values rise from about 2 to nearly 7, indicating a growing prevalence of stress, uncertainty, and food-related hardship. Compared to the idiosyncratic trend, this line is smoother and steeper, suggesting that households more uniformly perceive and report food insecurity under systemic conditions.

Finally, HDDS again shows a clear decline, falling from around 7 to just under 5. The drop is more linear and pronounced than in the idiosyncratic version, which reinforces the notion that systemic shocks have a stronger, more consistent impact on dietary diversity. This likely reflects disruptions in both physical access (market closures, transportation failures) and economic access (inflation, unemployment) that accompany such shocks.

Together, these plots suggest that while both types of shocks undermine food security, systemic shocks exhibit more uniform and severe effects, especially on dietary diversity and food consumption. In contrast, idiosyncratic shocks lead to more variable outcomes, which may be mediated by social capital, household buffers, or differential access to assistance.

Rising rCSI and FIES trends for both MSI types indicate that coping behaviors and subjective experiences respond similarly to both shock categories, but the magnitudes and slopes differ slightly. Systemic shocks seem to provoke broader and perhaps deeper household responses.

Moreover, the stronger and smoother relationships in the systemic panel may point to more predictable pathways of vulnerability—valuable for program design and early warning systems. Idiosyncratic shock patterns, while still meaningful, suggest a need for more targeted, household-level approaches.

These findings offer powerful visual evidence that both idiosyncratic and systemic shocks degrade food security across multiple dimensions—behavioral, experiential, and nutritional. However, systemic shocks produce more consistent and severe impacts, particularly on consumption and dietary diversity. Policymakers and program designers should take note of these distinctions. While systemic shocks may call for broad-based interventions (price stabilization, public works), idiosyncratic shocks may require individual-level support mechanisms, such as targeted cash transfers, social insurance, or case management.

Single-shock responses can systematically underestimate risk because they treat shocks as isolated events, when in practice households often face overlapping disruptions that reinforce each other. A compound-shock lens therefore has immediate operational value: it changes who is identified as high risk, when programs should scale up, and what combination of interventions is likely to work. The evidence from this analysis—showing progressively worse outcomes as households move from zero to one to two shocks within the same recall period—points to three policy shifts.

First, targeting systems should explicitly incorporate **compound exposure**, not only single-shock flags. Early warning tools and vulnerability dashboards typically track separate indicators (drought conditions, staple price inflation, flood alerts) and may trigger response when any one crosses a threshold. Yet the steepest welfare losses tend to appear where stressors overlap—such as “price + drought” contexts—because households simultaneously face weakened purchasing power and reduced food availability or income. Operationally, this implies moving from single-hazard maps to **co-exposure hotspotting**—that is, layering shocks to identify districts and livelihood zones where two (or more) stressors co-occur, and using these compound signals to prioritize geographic allocation and household triage when resources are constrained. This approach better reflects real-world interdependencies among hazards and the way risks cascade across systems (Adger, 2006; Heltberg et al., 2009).

Second, social protection should be designed for **multi-dimensional risk**, rather than relying on triggers or eligibility rules anchored to one shock type at a time. If compounding shocks are what drive the sharpest declines in food consumption and the most severe coping behaviors, then scale-up mechanisms for cash transfers, food assistance, or temporary fee waivers should incorporate **compound-shock indicators**—thresholds on an aggregated measure such as the MSI—to more reliably identify households likely to experience large consumption gaps and adopt harmful coping. Importantly, this is not only about improving prediction; it is about fairness and coverage. Because exposure is structurally patterned by assets, gender, and geography, single-shock triggers may repeatedly miss the same vulnerable groups who are systematically more likely to experience overlapping stressors (Barrett & Carter, 2013; Krishna, 2007). A multi-risk design therefore strengthens both targeting accuracy and equity.

Third, resilience programming must be **cross-sectoral** because shocks interact across systems, and siloed interventions risk addressing only one constraint while leaving the other binding. Agricultural measures—such as pest and disease management, drought-tolerant inputs, or veterinary support—are essential where production shocks are prominent, but they will often be insufficient in environments where households are also hit by market disruptions such as food and fuel price increases. Likewise, market stabilization and price monitoring can protect purchasing power, but will not restore production or livestock health when drought or disease constrains supply and incomes. The policy implication is to design resilience packages that match the compound reality: pairing agricultural support with market and safety-net measures in areas where climate and price shocks overlap, consistent with broader evidence on vulnerability and systemic interdependence (Adger, 2006; Heltberg et al., 2009).

The bottom line is straightforward: households rarely experience shocks in isolation, and this dataset shows that co-exposure to two shocks within the same recall period is consistently associated with worse food security outcomes across objective (FCS/HDDS), behavioral (rCSI), and experiential (FIES) measures. As climate variability and price volatility intensify, multi-risk-informed targeting, scalable social protection, and integrated resilience programming are not optional refinements—they are central to effective food security policy (Birkmann et al., 2013; FAO, 2021).

5. Discussion of findings

The findings from the non-parametric MSI analysis reveal important insights into the structure, drivers, and implications of multidimensional vulnerability among Nigerian households. Using the DIEM dataset, the study demonstrates how the MSI can move beyond descriptive profiling to serve as an outcome-anchored diagnostic tool for policy targeting and adaptive social protection.

Impact-based shock selection and construct validity

A central innovation of this study lies in the impact-based selection of shocks tied explicitly to FCS. Instead of relying on a priori classifications of what constitutes a “major” or “minor” shock, the selection process empirically identifies those shocks that exhibit a statistically significant association with reductions in FCS. This approach ensures that only welfare-relevant shocks contribute to the MSI, strengthening its construct validity. In practice, this means that the index is built not merely on perceived severity but on observed impact—an essential distinction for accurately mapping vulnerability. The result is a more meaningful alignment between the MSI and actual food security outcomes, allowing policymakers to focus interventions on the shocks that matter most to household welfare.

Superiority of the prevalence-weighted MSI

Among the three variants of the index—unweighted, population-weighted, and prevalence-weighted—the prevalence-weighted MSI consistently demonstrates superior performance across multiple validation metrics. Its stronger correlations with FCS, sharper mean separations at the severe food insecurity threshold (FCS < 21), and higher Spearman rank concordance indicate greater internal consistency and discriminatory power. The prevalence-weighting scheme gives proportionally higher influence to shocks that are more widespread, reflecting the reality that the social and market consequences of a shock often depend on its reach. In this way, the prevalence-weighted MSI captures not only individual exposure but also systemic exposure that can overwhelm community coping capacities. This feature makes it particularly useful for designing early warning systems and prioritizing geographic or demographic areas for intervention.

Systemic and compound shocks as primary drivers of decline

The analysis further distinguishes between idiosyncratic shocks—those affecting individual households—and systemic shocks—those affecting entire communities or regions. Results show that systemic shocks, especially when compounded with other stressors such as price surges, health emergencies, or conflict events, produce the steepest declines in FCS and HDDS and the most substantial increases in rCSI and FIES. This pattern highlights the amplifying effect of multiple concurrent shocks: when market disruptions, insecurity, and climate events occur together, coping mechanisms quickly become exhausted, and food consumption deteriorates across entire populations. The compound nature of these shocks also exposes gaps in the resilience architecture of social protection systems, which are often designed to respond to single, isolated events. Addressing systemic vulnerability, therefore, requires integrated risk management strategies that combine macroeconomic stabilization, livelihood diversification, and social safety nets capable of scaling during crisis periods.

Operational benchmarking and risk stratification

Beyond analytical refinement, the study translates the MSI into a practical policy instrument through a benchmarking framework that classifies households into four risk tiers based on the distribution of the index. These tiers—ranging from low-risk to extreme-risk—are defined using quartile-based cutoffs calibrated to observed food security outcomes. This operationalization transforms the MSI from a statistical construct into an actionable decision-support tool. For instance, households in the top quartile of the MSI distribution exhibit markedly lower FCS and HDDS and higher rCSI and FIES scores, indicating severe or chronic vulnerability. Such a gradient can inform targeting criteria for cash transfers, food aid, or resilience-building interventions. Moreover, by tracking changes in these quartile distributions over time, the MSI can support early warning systems and adaptive program scaling when households move into higher risk categories.

Implications for policy and future research

Together, these findings advance both the methodological and policy frontiers of shock analysis. The MSI provides a replicable, outcome-anchored framework that can be adapted across contexts while maintaining empirical rigor. For Nigeria, it offers a foundation for integrating multidimensional vulnerability assessment into national food security monitoring systems and the design of shock-responsive social protection programs. Future work should focus on dynamic applications of the MSI using panel data to capture recovery trajectories and persistence effects, as well as on exploring its predictive validity relative to alternative welfare indicators. In doing so, the MSI could evolve into a core tool for resilience analytics in the broader African food systems transformation agenda.

The MSI relies on self-reported household exposure to shocks over the previous 12 months. While such measures are widely used in vulnerability and resilience research, they are not without limitations. A growing literature compares subjective reports of shocks with instrument-based or satellite-derived measures and finds both convergence and divergence depending on context and shock type. For example, Linke, Witmer, and O'Loughlin (2020) show that household reports of drought exposure in Kenya partially align with meteorological indicators but may reflect livelihood impacts rather than strictly rainfall anomalies. Similarly, Solano-Hernandez et al. (2020) document substantial convergence between satellite drought indexes and farmers' perceptions in Patagonia, while noting that local production conditions shape reported experiences.

These findings suggest that self-reported shocks capture experienced and livelihood-relevant impacts, rather than purely physical hazard exposure. From a food security perspective, perceived and economically consequential shocks may be more relevant than objective climatic deviations alone. Nevertheless, self-reported data are subject to recall bias, salience effects, and heterogeneity in interpretation across respondents.

In this study, several design features mitigate these concerns. First, the 12-month recall window is standard in household vulnerability surveys and limits long-term recall error. Second, the MSI retains only shocks that demonstrate statistically significant associations with observed food security outcomes, thereby filtering out non-informative or weakly reported events. Finally, because the MSI is outcome-anchored, any systematic over- or under-reporting that does not correlate with welfare outcomes does not materially affect index construction.

Future research could extend this framework by triangulating survey-based shock exposure with geospatial rainfall, price, or conflict datasets to further assess measurement robustness.

6. Leveraging the non-parametric MSI for programming and policymaking in resilience building

In programming and policymaking for resilience-building, the non-parametric multi-shock index (MSI) emerges as a practical and analytically robust tool for identifying and responding to household vulnerability. Its design—anchored in observed exposure to shocks and devoid of heavy modeling assumptions—makes it especially valuable in fragile contexts characterized by limited data reliability, complex shock patterns, and high heterogeneity in household experiences. Because the MSI is derived directly from binary indicators of shock exposure, it remains intuitive and transparent, enhancing its usability across diverse policy and program environments.

Operationalizing the MSI begins with transforming it into decision-ready formats. One of the most immediate applications is in real-time targeting. Agencies can embed the MSI into interactive dashboards that visualize household vulnerability across geographic units, thereby supporting local governments and humanitarian actors in identifying priority areas. The index can also serve as an eligibility criterion in assistance programs, with thresholds established based on empirical distributions or policy priorities. Because of its validated correlation with food security outcomes—including Food Consumption Score (FCS), Household Dietary Diversity Score (HDDS), and the reduced Coping Strategies Index (rCSI)—the MSI offers a reliable foundation for targeting decisions in cash transfers, voucher systems, or in-kind food aid programs.

Importantly, the MSI supports differentiated or tiered response planning. Households with the highest MSI scores may be prioritized for immediate relief interventions, while those with moderate exposure could be directed toward livelihood support or adaptive safety nets. This allows for more strategic allocation of limited resources, ensuring that support is proportional to need. Furthermore, because the MSI can be disaggregated by household demographics such as gender or location, it facilitates the design of gender-sensitive and regionally tailored programs. For instance, if female-headed households consistently show higher MSI scores, this could inform targeted support measures in alignment with gender equity goals.

Beyond targeting, the MSI offers substantial value as a monitoring and evaluation tool. It can be used to establish pre-intervention baselines and to track resilience gains over time. Since it captures the compounded effect of multiple shocks, changes in MSI scores can be interpreted as improvements or deteriorations in a household's resilience profile. This positions the MSI as an important addition to resilience measurement frameworks. Unlike more data-intensive methods, the MSI can be generated regularly using short-form household surveys or mobile data collection platforms, enabling timely assessments and adaptive management.

From a policy perspective, the MSI can be embedded in national vulnerability assessments and early warning systems. It aligns well with the growing global emphasis on shock-responsive social protection, where programs are designed to expand vertically or horizontally in response to covariate shocks. The index can trigger such expansions, offering a justifiable and evidence-based rationale for scaling up support during crisis periods. In addition, it can facilitate coordination across sectors and agencies by offering a unified metric that reflects the cumulative effect of environmental, economic, and social shocks.

The scalability and adaptability of the MSI further enhance its policy relevance. Because it relies on non-parametric aggregation, the same methodology can be applied in other country contexts with minimal adjustments. By using local data to identify which shocks are associated with food insecurity and recalibrating prevalence weights accordingly, the MSI framework can be replicated across regions. This ensures that it retains both empirical relevance and operational simplicity, two qualities that are often difficult to reconcile in resilience analytics.

In sum, the non-parametric MSI offers a credible, scalable, and practical approach to diagnosing vulnerability and informing action. Its statistical validity, ease of interpretation, and strong association with key food security outcomes make it particularly suited to the policy and programmatic challenges of today's rapidly changing risk environments. As governments and partners seek to operationalize resilience in meaningful ways, the MSI provides a concrete mechanism for translating household-level data into actionable, equity-focused interventions.

Conclusion

Across low- and middle-income countries, the risk landscape facing households has shifted from episodic, single hazards toward overlapping and mutually reinforcing shocks—climate variability interacting with price volatility, conflict and displacement reshaping market access, and health or livelihood disruptions compounding existing vulnerability. In this setting, food security analysis and response systems that focus on one shock at a time can miss the way hardship is actually produced—not through a single event, but through the accumulation and interaction of stressors that erode consumption, exhaust coping capacity, and narrow diets. This broader reality motivates the core contribution of this paper: a non-parametric multi-shock index (MSI) that is intentionally assumption-light and operationally feasible, designed to summarize multiple-shock exposure in a way that remains interpretable for decision-making.

Nigeria serves here as a concrete application of that broader challenge. The country's mix of environmental volatility, macroeconomic pressures, and localized insecurity makes it an informative case for testing whether a multi-shock approach adds value beyond conventional single-shock monitoring. Using the Nigeria DIEM data, the results show a consistent pattern: as shock exposure rises—especially under compound and systemic shocks—food security outcomes worsen across multiple dimensions, including consumption quality and quantity (FCS), diet diversity (HDDS), coping intensity (rCSI), and lived experience of food insecurity (FIES). The Nigeria application therefore illustrates a general point with practical clarity: when households face multiple stressors within the same period, vulnerability is better captured by multi-shock exposure metrics than by isolated shock indicators.

A second conclusion concerns how multi-shock exposure should be summarized for applied use. Among the alternative MSI variants assessed, the prevalence-weighted index performs best in the Nigeria example, showing stronger discriminatory power and more stable gradients against food security outcomes. Interpreted in broader context, this finding suggests that in settings where systemic pressures are widespread—such as price surges or economy-wide disruptions—weights that reflect population prevalence can improve the index's usefulness for targeting and monitoring, because they capture shocks that signal shared constraints across households. This does not imply that rare shocks are unimportant; rather, it indicates that for operational ranking and risk profiling, a prevalence-weighted formulation can align well with how vulnerability is distributed under systemic stress.

Third, the paper underscores why non-parametric approaches are often the most appropriate starting point for multi-shock measurement in food security settings. Parametric methods can impose strong assumptions about functional form, separability, and additivity—assumptions that are difficult to justify when shock intensity, reporting, and interdependence vary across livelihoods and geographies. By contrast, the MSI framework remains transparent and empirically anchored, producing a tool that can be adapted to different survey modules and contexts without requiring a single "correct" model of how shocks translate into welfare loss.

Fourth, the Nigeria results point to an important conceptual distinction with program relevance: covariate (systemic) and idiosyncratic shocks can relate to food security outcomes differently. Systemic shocks—often reflected in price-related disruptions or widespread climatic stress—tend to shift the entire opportunity set households face, affecting both availability and access. More idiosyncratic shocks may be buffered or amplified depending on assets, livelihood strategies, and local support systems. Recognizing this difference is not academic hair-splitting; it affects the design of triggers, the composition of response packages, and expectations about who can recover quickly versus who may face persistent food insecurity (Adger, 2006; Heltberg et al., 2009).

Fifth, the application suggests that while a single MSI is useful for summary monitoring and ranking, fine-tuning is advisable when policy decisions depend on specific mechanisms of vulnerability. The observed variation across compound shock combinations, together with patterns associated with gender and household characteristics, implies that a headline MSI may be strengthened by complementary diagnostics—such as flags for particularly damaging shock pairings or subgroup-sensitive interpretations. In practice, this supports a two-tier approach: a parsimonious MSI for routine monitoring and targeting, paired with a small number of context-specific overlays for program design and risk mitigation.

Finally, Nigeria should be read as an illustrative implementation, not a boundary condition. The next steps that would most advance this work are (i) replication across countries to test portability of shock selection and weighting under different risk regimes, and (ii) panel data applications to move beyond co-exposure in a recall period toward sequencing, persistence, and recovery dynamics—capturing when shocks truly compound over time and how resilience trajectories diverge. These extensions would strengthen external validity and increase the MSI's value for adaptive social protection and anticipatory action systems (Birkmann et al., 2013; FAO, 2021).

Taken together, the broader message is that multi-shock exposure is not a niche concern—it is increasingly the *normal* operating environment for poor and food-insecure households. The MSI framework offers a pragmatic bridge between this complexity and policy action, and the Nigeria application demonstrates how a prevalence-weighted, non-parametric approach can translate multi-risk reality into decision-ready evidence.

References

Acemoglu, D., Ozdaglar, A., & Tahbaz-Salehi, A. (2015). Systemic risk and stability in financial networks. *American Economic Review, 105*(2), 564–608. https://doi.org/10.1257/aer.20130456

Adger, W. N. (2006). Vulnerability. *Global Environmental Change, 16*(3), 268–281. https://doi.org/10.1016/j.gloenvcha.2006.02.006

Barrett, C. B., & Carter, M. R. (2013). The economics of poverty traps and persistent poverty: Empirical and policy implications. *Journal of Development Studies, 49*(7), 976–990. https://doi.org/10.1080/00220388.2013.785527

Barrett, C. B., & Santos, P. (2014). The impact of changing rainfall variability on resource-dependent wealth dynamics. *Ecological Economics, 105*, 48–54.

Birkmann, J., Cardona, O. D., Carreño, M. L., Barbat, A. H., Pelling, M., Schneiderbauer, S., … Welle, T. (2013). Framing vulnerability, risk and societal responses: The MOVE framework. *Natural Hazards, 67*(2), 193–211. https://doi.org/10.1007/s11069-013-0558-5

Booysen, F., Van Der Berg, S., Burger, R., Von Maltitz, M., & Du Rand, G. (2008). Using an asset index to assess trends in poverty in seven Sub-Saharan African countries. *World Development, 36*(6), 1113–1130. https://doi.org/10.1016/j.worlddev.2007.10.008

Carter, M. R., Little, P. D., Mogues, T., & Negatu, W. (2007). Poverty traps and natural disasters in Ethiopia and Honduras. *World Development, 35*(5), 835–856. https://doi.org/10.1016/j.worlddev.2006.09.010

De Bandt, O., & Hartmann, P. (2000). *Systemic risk: A survey* (Working Paper Series No. 35). European Central Bank. https://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp035.pdf

Dercon, S. (2002). Income risk, coping strategies, and safety nets. *World Bank Research Observer, 17*(2), 141–166. https://doi.org/10.1093/wbro/17.2.141

Devereux, S. (2001). Livelihood insecurity and social protection: A re-emerging issue in rural development. *Development Policy Review, 19*(4), 507–519. https://doi.org/10.1111/1467-7679.00148

Food and Agriculture Organization of the United Nations. (2011). *Guidelines for measuring household and individual dietary diversity*. FAO.

Food and Agriculture Organization of the United Nations. (2016). *Resilience Index Measurement and Analysis II (RIMA-II)*. https://www.fao.org/3/i5665e/i5665e.pdf

Food and Agriculture Organization of the United Nations. (2018). *The State of Food Security and Nutrition in the World 2018: Building climate resilience for food security and nutrition*. FAO.

Food and Agriculture Organization of the United Nations. (2021a). *The State of Food and Agriculture 2021: Making agrifood systems more resilient to shocks and stresses*. FAO.

Food and Agriculture Organization of the United Nations. (2021b). *The State of Food Security and Nutrition in the World 2021*. https://doi.org/10.4060/cb4474en

Food and Agriculture Organization of the United Nations. (2025). *Data in Emergencies (DIEM) information hub*. https://data-in-emergencies.fao.org/

Food and Agriculture Organization of the United Nations, International Fund for Agricultural Development, United Nations Children's Fund, World Food Programme, & World Health Organization. (2023). *The state of food security and nutrition in the world 2023*. FAO.

FEWS NET. (2018). *Elevated food security outcomes persist again in 2018 in the northeast during the harvest season* (Food Security Outlook). https://fews.net/west-africa/nigeria/food-security-outlook/october-2018

Headey, D., & Ruel, M. (2020). *Economic shocks and child wasting* (IFPRI Discussion Paper No. 01941). International Food Policy Research Institute. https://doi.org/10.2499/p15738coll2.133786

Heltberg, R., Siegel, P. B., & Jorgensen, S. L. (2009). Addressing human vulnerability to climate change: Toward a "no-regrets" approach. *Global Environmental Change, 19*(1), 89–99. https://doi.org/10.1016/j.gloenvcha.2008.11.003

Hoddinott, J., & Quisumbing, A. (2003). *Methods for microeconometric risk and vulnerability assessments* (Social Protection Discussion Paper Series). World Bank.

International Monetary Fund. (2020). *Global Financial Stability Report: Markets in the time of COVID-19*. https://www.imf.org/en/Publications/GFSR

Intergovernmental Panel on Climate Change. (2022). *Climate change 2022: Impacts, adaptation and vulnerability*. Cambridge University Press.

Johnson, N. L., Kovarik, C., Meinzen-Dick, R., Njuki, J., & Quisumbing, A. (2016). Gender, assets, and agricultural development: Lessons from eight projects. *World Development, 83*, 295–311. https://doi.org/10.1016/j.worlddev.2016.01.009

Kogo, B. K., Kumar, L., & Koech, R. (2021). Climate change and variability in sub-Saharan Africa: A review of impacts on agriculture and food security. *Environment, Development and Sustainability, 23*(2), 1559–1585. https://doi.org/10.1007/s10668-020-00589-1

Krishna, A. (2007). Poverty and health: Defeating poverty by going to the roots. *Development, 50*, 63–69. https://doi.org/10.1057/palgrave.development.1100359

Linke, A. M., Witmer, F. D. W., & O'Loughlin, J. (2020). Do people accurately report droughts? Comparison of instrument-measured and national survey data in Kenya. *Climatic Change, 162*(3), 1143–1160. https://doi.org/10.1007/s10584-020-02724-3

Maxwell, D., & Caldwell, R. (2008). *The coping strategies index: Field methods manual*. CARE & World Food Programme.

Maxwell, D., Vaitla, B., & Coates, J. (2014). How do indicators of household food insecurity measure up? An empirical comparison from Ethiopia. *Food Policy, 47*, 107–116. https://doi.org/10.1016/j.foodpol.2014.04.003

Maxwell, D., Vaitla, B., Tesfay, G., & Abadi, N. (2014). *Resilience, food security dynamics, and poverty traps in Northern Ethiopia*. Feinstein International Center, Tufts University.

Maxwell, D., Webb, P., Coates, J., & Wirth, J. (2003). *How do different indicators of household food security compare?* Food and Nutrition Technical Assistance Project. https://fic.tufts.edu/wp-content/uploads/Different-Indicators-of-HFS.pdf

Save the Children. (2020). *The hidden impact of COVID-19 on children*. Save the Children International.

Solano-Hernandez, A., Bruzzone, O., Groot, J., Laborda, L., Martínez, A., Tittonell, P., & Easdale, M. H. (2020). Convergence between satellite information and farmers' perception of drought in rangelands of North-West Patagonia, Argentina. *Land Use Policy, 97*, Article 104289.

World Food Programme. (2008). *Food consumption analysis: Technical guidance sheet*. WFP.

World Bank. (2018). *Adaptive social protection: Building resilience to shocks*. https://openknowledge.worldbank.org/handle/10986/29115

World Bank. (2023). *Poverty and Inequality Platform: Nigeria*. https://pip.worldbank.org/

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