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Reimagining Food Crises: Archetypes, Collapsing Recovery Gaps, Crisis Staircases, and Recovery Traps

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Abstract

Acute food insecurity affects over 295 million people globally, yet crisis trajectories remain poorly understood. We analyze 1,658 crisis episodes from the Harmonized Food Insecurity Dataset spanning 13 years across 49 countries, identifying eight distinct archetypes that reveal food crises follow predictable trajectories. Seasonal crises dominate (73%), while protracted emergencies account for only 5.9% of episodes. We find a striking asymmetry in phase transitions: in severe crises, recovery is 7 times more likely than escalation (95% CI: 5.8–8.7), but recovery probability degrades with duration, from 20% to under 2% over 24 months. Repeated seasonal crises accumulate into prolonged states through a "crisis staircase" effect. Recovery windows between crises have compressed from 40 months to 4 months over the study period, with a 4–6-month post-crisis period associated with the highest risk of escalation. These findings reframe food crisis response from reactive intervention to trajectory-informed anticipatory action.

Introduction

Humanitarian funding has plummeted at a time when acute food insecurity affects over 295 million people globally[1]. Understanding how food crises incubate[2] and evolve has never been more important for preventing famines. Yet, despite unprecedented investment in food security monitoring, including the Integrated Food Security Phase Classification (IPC), the Famine Early Warning Systems Network (FEWS NET), and real-time monitoring, policy responses remain largely reactive rather than anticipatory, focused on resilience-building, and aligned with food crisis dynamics[3–5].

Current early warning systems have made significant progress in detecting crisis onset and classifying severity, but provide little guidance on trajectory, and prediction remains challenging[6–8]. Policymakers face key questions that monitoring data alone cannot answer: Will this crisis escalate or resolve? How long will it persist? When is intervention most likely to promote recovery? The absence of a systematic framework for understanding crisis dynamics hampers the targeting of humanitarian response and resilience programming, undermining progress towards Sustainable Development Goal 2 (Zero Hunger)[9,10].

Previous research defined famine and examined food security patterns at national scales or within specific contexts[11–15], but a comprehensive analysis of subnational crisis trajectories across diverse settings has been limited by data fragmentation. While case studies have characterized specific famines[13,16,17], and statistical approaches have improved crisis prediction[17], no systematic typology of crisis trajectories exists to guide differentiated responses.

The recent publication of the Harmonized Food Insecurity Dataset (HFID)[18], which integrates IPC, *Cadre Harmonisé*, and FEWS NET data into a consistent time series, now enables systematic analysis of crisis dynamics. The IPC area classification system uses standard indicator benchmarks to categorize each geographical area into Phase 1 (Minimal), Phase 2 (Stressed), Phase 3 (Crisis), Phase 4 (Emergency), or

Phase 5 (Catastrophe/Famine) when 20% of the population in the area meets the benchmarked criteria[3]. A food crisis (IPC Phase 3+) occurs when households cannot meet their basic food needs without depleting assets such as livestock or savings, skipping meals, or when acute malnutrition, particularly among children, rises to dangerous levels[3,14]. Famines represent the most severe form of food crisis[11,14,16]. Using the HFID allows for the identification of temporal patterns across past crises to inform humanitarian policy and decision-making.

This paper asks: **what are the temporal patterns of food crises across food-insecure countries, and how can understanding them improve anticipatory action, crisis management, and resilience-building?**

The findings reveal that while food security conditions tend to persist, the phase transitions of severe food crises (IPC4+) are strongly asymmetric: recovery is 7 times more likely than escalation. This recovery tendency degrades rapidly and repeated food crises can lead to more severe, persistent crisis states, creating narrow intervention windows that align with natural system resilience when timed appropriately[19–21]. Our analysis reveals marked patterns in duration, severity, and volatility across crisis episodes, suggesting an eight-archetype typology with distinct transition dynamics between crisis phases.

Results

Eight distinct archetypes characterize food security crises

We identified 1,658 discrete crisis episodes from the monthly subnational Harmonized Food Insecurity Dataset (HFID), spanning 2011–2024 across 49 countries (see Methods for episode definition and classification procedures). These episodes were classified into eight archetypes using duration, peak severity, and phase volatility (Table 1, Fig. 1).

The dominant archetype is the seasonal crisis (72.6% of episodes), characterized by short duration (median 3 months, IQR: 2–5), moderate severity (Phase 3), and low volatility. These crises follow predictable agricultural calendars, peaking during lean seasons and resolving with harvests. Their prevalence aligns with recent practices of lean-season assistance programs and social protection systems to address persistent food insecurity and extreme poverty[22–24].

At the opposite extreme, protracted emergencies (5.9% of episodes) persist for years (median 67 months, IQR: 42–89) at severe (Phase 4) or extreme (Phase 5) levels. This food crisis archetype is concentrated in conflict-affected settings, including South Sudan, Yemen, and parts of the Democratic Republic of Congo, where underlying drivers prevent recovery regardless of humanitarian intervention[13,25–27].

Between these poles lie six intermediate archetypes. Prolonged moderate crises (13.5% of episodes) maintain stable Phase 3 conditions for 12 to 36 months without escalating to emergency (Phase 4) levels. Entrenched moderate crises (2.3%) persist beyond 36 months at Phase 3. Rapid-onset crises

(3.2%) escalate quickly to peak severity before gradually recovering, whereas escalating crises (0.4%) show progressive worsening trajectories. Oscillating crises (1.0%) exhibit volatile phase changes, often reflecting conflict dynamics or repeated shocks. Finally, severe shocks (1.1%) reach Phase 4 or 5 briefly before rapid resolution.

Repeated crises can escalate towards persistence

Among 222 locations (Extended Data Fig. 1) experiencing three or more crises, we identified a "crisis staircase" effect where repeated seasonal crises accumulate into more prolonged states. The most common multi-step deterioration pathway is [seasonal crisis] → [prolonged moderate] → [protracted emergency]. 10 locations completed this full pathway, while 114 locations showed seasonal crises eventually transitioning to a prolonged moderate state, and 81 locations showed double-seasonal episodes before transitioning to a prolonged moderate state. Recovery from these archetypes to seasonal patterns is rare. Only 10 locations showed de-escalation from protracted or entrenched crises to seasonal crises. These locations were concentrated in Zimbabwe, where 6 provinces recovered following stabilization. By the end of the dataset period, 14.9% of multi-episode locations remained trapped in protracted emergency or entrenched moderate states. These transition patterns suggest that, if not addressed, each seasonal crisis increases the risk of transitioning to a more intractable crisis type.

To visualize these transitions over time, we tracked the dominant crisis archetype for each location across consecutive periods from 2011 to 2023 (Fig. 2). This alluvial diagram reveals a progressive accumulation of non-seasonal crisis states: prolonged moderate crises grew from 5 locations in 2011–2013 to 64 by 2020–2022, while protracted emergencies expanded from 4 in 2011 to 44 by 2022. Crucially, the transition flows are asymmetric, between 2017–2019 and 2020–2022, 63 locations escalated to more severe archetypes while only 12 de-escalated, a 5:1 ratio. The most recent transition (2020–2022 to 2023) shows partial reversal, with 25 de-escalations against 8 escalations, though 163 locations persisted in their existing archetype, indicating that crisis states, once established, tend to endure. Whether these patterns continue given the dramatic reduction in humanitarian assistance and monitoring coverage in 2025 remains an open question[28].

Recovery windows between crises are compressing

The intervals between successive crisis episodes, or recovery gaps when food security temporarily improves to Phase 2 or below, have collapsed. Among 284 locations experiencing multiple crises, mean gap duration declined from 40 months in 2011 to 4 months by 2023 (Fig. 4a). This 10-fold compression is not an artifact of monitoring expansion. Analysis restricted to 73 locations monitored continuously in both early (2011–2015) and late (2020–2023) periods shows similar compression from 55 to 4 months, and 80% of individual locations show within-location gap shrinking over time.

Gap duration following a crisis predicts the severity of subsequent episodes. Transitions following gaps of 4 to 6 months show the highest IPC phase escalation rate (13.1%), compared to 5.9% for very short gaps (0 to 3 months) and 2.6% for gaps exceeding 24 months (Fig. 4b). The lower escalation rate for

very short gaps reflects multimodal food stress patterns rather than classical seasonality. These brief gaps concentrate in regions with multiple annual stress peaks (the DRC accounts for 27% of cases) and areas where food stress is decoupled from rainfall patterns, such as Afghanistan (26%). In these contexts, 74% of 0 to 3-month gap transitions return to the same archetype, representing rapid cycling between predictable stress peaks. The 4 to 6-month window, by contrast, represents a pivotal vulnerability period: long enough for crisis characteristics to evolve, but too short for full livelihood recovery. This window shows the highest escalation rate and the greatest absolute number of crisis transformations from seasonal to persistent patterns (n = 49), making it the primary period during which crises shift trajectory.

Geographic patterns in gap duration reveal distinct vulnerability profiles. Central Africa shows the shortest mean gaps (5.7 months), driven by the Democratic Republic of Congo, where 12 locations cycle through crises every 2–4 months. West Africa experienced the most dramatic compression, from 42 months in 2011–2017 to 6 months in 2020–2023. The Horn of Africa shows moderate gap duration (15.5 months) but the highest escalation rates when crises return, with South Sudan (30%) and Sudan (26%) showing particularly elevated risk. Notably, the DRC, despite having the shortest gaps, shows only 1% escalation rate, suggesting that rapid cycling at stable severity levels represents a distinct pattern from escalating crisis sequences.

Recovery from emergency and famine is systematically favored over escalation

Analysis of month-to-month phase transitions reveals a fundamental asymmetry in crisis dynamics. While persistence dominates, recovery is consistently more likely than escalation (Fig. 3). This asymmetry is increasingly pronounced at the higher severity levels. At the boundary between Phase 3 (Crisis) and Phase 4 (Emergency), the monthly probability of recovery (Phase 4 to Phase 3) is 13.7% (95% CI: 11.7–15.9%), while the probability of escalation (Phase 3 to Phase 4) is only 2.0% (95% CI: 1.6–2.3%); a ratio of 7.0:1 favoring recovery (95% CI for ratio: 5.8–8.7). Escalation from Phase 4 to Phase 5 (Famine) is rare and occurs in only 0.17% of Phase 4 observations, while recovery from Phase 5 to Phase 4 occurs at 9.1% monthly probability.

The asymmetry towards recovery is robust across temporal and spatial scales. Quarterly aggregation of the same data yields a recovery ratio of 6.0:1 (95% CI: 4.9–7.3), lower than the monthly estimates due to the coarser temporal resolution, but still strongly favors recovery. Analysis at finer spatial resolution (administrative level 2) produces a stronger asymmetry (recovery ratio 11.5:1), likely reflecting the averaging effect of admin1 aggregation. The finding holds across all seven regions analyzed, though its magnitude varies substantially: from 3.6:1 in the Horn of Africa (95% CI: 2.7–5.2; n = 168 locations) to 37.8:1 in Southern Africa (95% CI: 20.6–130.9; n = 69 locations). Regions with higher conflict exposure (Horn of Africa, Central Africa) show weaker asymmetries, consistent with conflict impeding recovery.

The asymmetry suggests that food systems possess inherent resilience that tends towards recovery when acute stressors abate[20,21]. Notably, 79% of locations reaching Phase 4 have only one episode; repeat Phase 4 crises follow two distinct patterns: chronic severe settings (DRC, Afghanistan), where

back-to-back emergencies occur with minimal gaps, and shock-prone locations (primarily Somalia), where the same areas are repeatedly affected by discrete regional shocks separated by years of seasonal patterns. However, this natural recovery tendency operates within constraints. Persistent structural factors, particularly active conflict, suppress recovery mechanisms, explaining why protracted emergencies persist despite favorable recovery probabilities[25,27,29]. Finally, and perhaps most hopeful, the longer a location is in Phase 1, the lower the likelihood of deterioration, possibly because households have time to build assets and resilience.

Phase 3 is a sticky state

While the Phase 4→3 boundary shows strong asymmetry towards recovery (7.0:1), the Phase 3→2 boundary tells a different story. Monthly recovery probability from Phase 3 (Crisis) to Phase 2 (Stressed) is 6.8% (95% CI: 6.1–7.5%), while escalation from Phase 2→3 occurs at 5.7% (95% CI: 5.2–6.2%), an asymmetry ratio of only 1.2:1 (95% CI: 1.1–1.3). This 1.2:1 ratio measures the relative ease of crossing the Phase 3/2 threshold in either direction. A separate metric, the ratio of recovery (to Phase 2) versus escalation (to Phase 4) among months at Phase 3 is higher, indicating that recovery is more probable than escalation within Phase 3. However, this within-phase balance differs from the boundary-crossing asymmetry that defines stickiness: while populations at Phase 3 are unlikely to escalate to Phase 4, they are also unlikely to recover to Phase 2. Thus, Phase 3 can be viewed as a "sticky state", acting like a pseudo-attractor pulling trajectories towards it, likely affected by multiple poverty traps[19,30,31].

This stickiness has important implications. The robust 7:1 asymmetry at the Phase 4 threshold indicates that most emergency conditions tend to resolve relatively quickly. However, populations may remain at Phase 3 for extended periods, unable to recover to Phase 2 without significant support. This pattern is consistent with the observation that prolonged moderate crises (13.5% of episodes) maintain stable Phase 3 conditions for 12–36 months.

Recovery probability degrades with crisis duration

Recovery rates decay sharply as crises persist, creating a time-dependent window for effective intervention (Fig. 3d–e). For crises at Phase 4, the monthly probability of recovery to Phase 3 is 20.0% (95% CI: 16.8–23.0%) during the first three months. This probability declines to 12.2% (95% CI: 9.5–15.2%) at 7–12 months, 9.0% (95% CI: 5.9–12.8%) at 13–24 months, and only 1.6% (95% CI: 0.0–3.2%) after 24 months. The decay follows an approximately exponential pattern ($R^2 = 0.95$), with the sharpest decline concentrated after the first year.

Early intervention, during the first months of a crisis or a crisis escalation, aligns with the peak probability of natural recovery. Delayed responses face compounding disadvantages; not only has the crisis persisted longer, but the system's capacity for recovery has diminished. A similar but more pronounced degradation occurs at Phase 3. Recovery probability from Phase 3 to Phase 2 decays from 11.4% (95% CI: 10.2–12.7%) in the first 1–3 months to just 1.3% (95% CI: 0.8–1.9%) after 24 months, with a crossover point, where escalation probability exceeds recovery probability, at approximately 29

months (95% CI: 25–34). Even in the first three months, P(3→2) is only 11.4% versus P(3→4) of 1.9%, giving a within-phase ratio of ~6:1 that is already much weaker than the Phase 4→3 recovery asymmetry. The combination of lower baseline asymmetry (1.2:1 vs 7:1) and faster degradation makes Phase 3 a potential "trap state" in which populations can remain indefinitely without progressing to emergency conditions or recovering to stressed conditions.

The mechanism underlying recovery degradation likely involves asset depletion and livelihood erosion[19,20,30]. Households in early-stage crisis may retain productive assets and social networks that enable recovery when conditions improve. As a crisis persists, these buffers erode: livestock are sold, savings exhausted, social networks strained, and children's development compromised[30,31]. Each month of crisis reduces the capacity for autonomous recovery, shifting the burden increasingly to external intervention. In contrast, the decreasing likelihood of deterioration the longer an area is in Phase 1 suggests that the process works in reverse as people recover assets, accumulate reserves, and become more resilient.

This time-dependence helps explain why the same recovery asymmetry can coexist with protracted emergencies. The 7:1 recovery ratio applies to the average crisis month; however, crises that persist beyond 24 months exhibit recovery probabilities below 2%. At these rates, even favorable asymmetry translates to expected crisis durations measured in years.

Temporal trends reflect monitoring expansion rather than severity change

Comparing trends in the data requires careful interpretation (Extended Data Table 1). Phase 4+ rates changed from 1.7% to 4.6% across all locations in aggregate. However, this comparison is confounded by substantial changes in monitoring coverage. The number of monitored locations expanded from 492 to 739, with 253 new locations entering monitoring in the late period.

To test whether observed changes reflect genuine trends or composition effects, we conducted a matched-location analysis restricted to the 486 locations monitored in both the first and second half of the dataset. Among matched locations, Phase 4+ rates increased from 1.7% to 4.8%. The 253 new locations that entered monitoring in the late period had a Phase 4+ rate of 3.6%, below the matched-location rate, meaning that monitoring expansion partially diluted the apparent trend in aggregate data. Among the 359 locations with the most consistent monitoring (observed in 12 or more of the 14 years), Phase 4+ rates increased from 1.4% to 3.9%, confirming a genuine upward trend in severity. Only 6 locations dropped out of monitoring between periods, all with 0% Phase 4+ rates, indicating that attrition did not bias the comparison.

This finding has important methodological implications. Cross-sectional comparisons of food security trends must account for changing monitoring coverage. The consistent increase in Phase 4+ rates across matched locations suggests a genuine worsening of crisis severity over the study period, though changes in aggregate rates also reflect composition effects from monitoring expansion.

To further disentangle monitoring expansion from genuine escalation, we repeated the archetype transition analysis using only the fixed cohort of 395 locations monitored in 2016 (Extended Data Fig. 2). This cohort-controlled analysis eliminates the effect of new locations entering the dataset. Within this fixed cohort, non-seasonal crisis locations grew from 28 (2011–2013) to 156 (2020–2022), a 6-fold increase with no change in monitoring footprint. Protracted emergencies within the cohort grew from 4 to 49 locations. The annual transition flows confirm that 2020–2021 during the peak of the COVID-19 pandemic[32,33] was the peak escalation year, with 46 locations worsening versus only 4 recovering (11.5:1 ratio). While monitoring expansion accounts for approximately 65% of the absolute growth in crisis location counts, the crisis staircase pattern, progressive accumulation of persistent and protracted states, is robust to this correction.

Recent years have nonetheless seen concerning developments. Sudan and South Sudan show clear deterioration trends, and the 2021–2024 period saw 47 Phase 4+ episodes concentrated in Afghanistan, Somalia, Sudan, and the DRC. These country-specific trajectories presaged the extreme levels of food crisis observed in 2025 in many of these areas[1,34–36].

Discussion

Our analysis reveals that food crises follow predictable patterns that differ markedly from prevailing narratives of chronic emergency. Four findings have critical implications for policy and practice.

First, the dominance of seasonal crises (~73% of all crises) indicates that most food crises follow agricultural calendars in predictable locations. This predictability creates opportunities for targeting of resilience-building, as well as for shock-responsive social protection systems that leverage efficient, pre-arranged finance and anticipatory action[37–39]. Countries with high proportions of seasonal crises (much of the Sahel, Central America, parts of South Asia) are particularly suitable for these approaches[40,41]. The timing of interventions can be optimized throughout the year, aligning seasonal stress with periods when people can invest in efforts to build resilience and when anticipatory action can blunt the impact of recurrent shocks. Recent evidence suggests anticipatory action can reduce humanitarian costs by up to 50%[40].

Second, the strong recovery asymmetry (7:1 at the Phase 3→4 threshold) suggests that humanitarian response should support natural recovery both at the onset of a crisis and as it deteriorates. In other words, humanitarians should focus on enabling the conditions under which inherent resilience can operate[20,21]. Livelihood protection may be as important as direct food assistance, because preserving household assets maintains recovery capacity[19,20]. Cash transfers that provide affected people with greater flexibility may better support recovery[42–44]. Market systems interventions to support small and medium-sized enterprises in restarting operations as soon as possible, providing services, employment, and income generation[45–48], may also reinforce natural recovery tendencies and reduce transitions to more persistent food crisis states.

Third, recovery degradation creates urgency for early action, especially as crises deteriorate. The monthly decline from 20% to 2% in recovery probability over 24 months quantifies the cost of delayed response. This finding supports the economic case for anticipatory and early action that accelerates recovery, not just saves lives[39,49]. Early intervention succeeds in contexts with high recovery probability, whereas late intervention must overcome degraded system capacity. The cost-per-beneficiary for early action may be substantially lower, as interventions in high-recovery contexts (20% probability) leverage natural resilience rather than substituting for it, consistent with estimates suggesting anticipatory action reduces humanitarian costs by 30–50% compared to conventional response[37,40,50]. The Grand Bargain commitment to increase investment in early action aligns with these findings while current hyper-prioritization efforts may work against these tendencies[51–53].

Fourth, the compression of recovery gaps between 2011 and 2024, from 40 months to 4 months, indicates that crisis cycles are accelerating. Populations now have less time to rebuild assets and restore livelihoods between shocks, consistent with evidence of eroding household resilience in frequently affected regions. The 4 to 6-month post-crisis window emerges as a critical intervention point, as this period exhibits the highest risk of crisis transformation from seasonal to persistent patterns. Investments in post-crisis recovery, livelihood restoration, asset rebuilding, and market rehabilitation, during this narrow window, may be essential to prevent the accumulation of seasonal crises into protracted states. This insight is also an important finding for social protection systems, suggesting that designing support to solidify recovery during this period could provide significant benefits and long-term savings. Overall, it complements the case for early action during crises with an equally urgent case for sustained engagement after crises formally end. The dramatic reduction in humanitarian funding, between 2023 and 2024 may result in substantially higher transition rates into protracted, more severe crisis states in the coming years, as hyper-prioritization of humanitarian aid limits resources precisely in these windows[50,51,53].

Our findings also highlight the limits of anticipatory and early-action approaches. Both the stickiness of recovery from Phase 3 to Phase 2 and the crisis staircase effect illustrate the importance of concentrated, deliberate, multi-year approaches that help move people out of food crises and prevent escalations into protracted states. These approaches are essential to global efforts to reduce humanitarian needs[54].

In addition, protracted emergencies, although rare (~5.9% of episodes), account for a disproportionate humanitarian burden[55,56] and resist resolution regardless of intervention timing[57,58]. These crises concentrate in conflict settings where the underlying drivers of food insecurity cannot be addressed through humanitarian means alone[59–61]. For protracted emergencies, the policy implication is not earlier action but rather conflict resolution and political stabilization[62,63], which humanitarian actors cannot deliver, even as humanitarian action remains essential to minimizing suffering and loss to the maximum extent possible[64].

Our typology provides a framework for matching response strategies to crisis characteristics (Table 2). Seasonal crises warrant systemic responses such as shock-responsive social protection programs to protect vulnerable households and build resilience. Pre-arranged and forecast-based financing can ensure additional resources are in place to limit the impact of large shocks in areas prone to seasonal crises. Predictable cash transfers timed to lean seasons can prevent asset depletion[23,44]. These interventions work with high natural recovery probability. Rapid onset events (3%) require surge emergency response capacity. Pre-arranged finance, pre-positioned resources, and rapid deployment mechanisms are essential here too[39]. The short duration means intervention windows are narrow, but recovery probability remains high. Prolonged moderate crises (14%) benefit from focused multi-year resilience-building investments that address underlying vulnerabilities rather than repeated emergency responses and prevent deterioration to more severe states. Graduation programming[65], landscape and ecosystem restoration[66,67], and livelihood diversification[68] can build resilience against seasonal stress. Protracted emergencies (~6%) require sustained humanitarian commitment alongside efforts to address root causes. The degraded recovery probabilities found in protracted crises mean external support must substitute for, not merely support, natural recovery. These contexts demand realistic expectations: resolution depends on political change beyond the control of humanitarian actors. Escalating crises (0.4%), though rare, demand immediate attention. Our analysis shows that crises with expanding geographic extent are strongly predictive of worsening trajectories; spatial expansion should trigger response escalation. Finally, policymakers must continue efforts to support recovery and resilience in the critical 4–6-month period after an area exits a food crisis to consolidate recovery and limit the risks that the area returns to a more protracted and severe food crisis.

Several limitations warrant consideration concerning the IPC classification system, geographical bias towards humanitarian priority areas, episode detection, and sample size for the pattern of progressively worsening through repeated transitions (i.e. crisis staircase). These limitations are discussed in the methods section. However, this study identifies important patterns in food crises across food-insecure countries that can inform changes in policy and practice to facilitate anticipatory action, food crisis management and recovery, and resilience-building strategies towards the vision of zero hunger. The high recovery asymmetry (7.0:1) offers grounds for measured optimism. Food systems are not inevitably sliding towards catastrophe but possess inherent tendencies towards stability. Effective policy should work with these tendencies, creating conditions for recovery and resilience rather than attempting to impose resolution. The narrow intervention window identified by recovery degradation makes timing critical, but when timing is right, the odds favor success.

Methods

Data source

We used the Harmonized Food Insecurity Dataset (HFID) version 1.1.1[18], which integrates Integrated Food Security Phase Classification (IPC), Cadre Harmonisé (CH), and Famine Early Warning Systems

Network (FEWS NET) food security assessments into a consistent monthly time series at subnational (administrative level 1) resolution. The dataset covers June 2007 through May 2024 across 80 countries, with 311,838 location-month observations. Although the HFID covers 2007–2024, subnational monitoring coverage sufficient for episode detection begins in 2011, when the number of area-month observations increases by an order of magnitude.

When multiple data sources existed for the same location-month, we prioritized FEWS NET classifications given their longer continuous time series spanning the full study period (2011–2023) and consistent methodology across regions; IPC/CH coverage is more variable, with many countries having assessments beginning only after 2015. Sensitivity analysis using IPC-priority classification showed similar recovery ratios (6.6:1 vs 7.0:1; Extended Data Table 2).

We assessed data source consistency by comparing FEWS NET and CH/IPC classifications where both exist (Extended Data Table 4). We also benchmarked IPC area classifications against food security input indicators using IPC Technical Manual thresholds.

The IPC classification system, while standardized, involves subjective judgment and may not be perfectly comparable across contexts or time periods[69,70]. Where FEWS NET and IPC/Cadre Harmonisé (CH) classifications coexist for the same area-month (n = 12,617), they agree within one phase in 96% of cases, but IPC/CH systematically classifies higher than FEWS NET (mean difference 0.4 phases). Because IPC/CH coverage expanded substantially during 2017–2020 (Extended Data Table 4), this transition may introduce temporal heterogeneity into the combined time series, though our matched-location analysis (Extended Data Table 1) controls for this by comparing the same locations across periods. Comparison of IPC area classifications against food security input indicators (Food Consumption Score, Reduced Coping Strategy Index) reveals that area classifications are systematically more conservative than these indicators alone would imply (Extended Data Table 4), suggesting our crisis episodes represent lower-bound severity estimates[69]. Data coverage varies geographically, with stronger representation in humanitarian priority regions. The 12-month interpolation threshold used to bridge data gaps introduces uncertainty in episode boundaries, though sensitivity analysis confirms results are robust to thresholds of 6 and 18 months (Extended Data Table 3).

Data analysis workflow

Data management and exploration were supported by a custom research environment integrating a Directus database (Railway) with document management (Zotero) and Python analytical tools. The Harmonized Food Insecurity Dataset (HFID v1.1.1; 311,838 observations) was imported into this structured database to enable flexible querying. Crisis episode detection algorithms and the 8-archetype classification system were developed by the authors through iterative analysis, with computational implementation in Python. All methodological decisions, including threshold selection, archetype definitions, and interpretation of transition dynamics, were made by the authors based on domain expertise and literature review. Validation comprised 1,700 test cases, achieving 100% reproducibility.

Figures were generated programmatically using matplotlib and seaborn. Claude Code (Anthropic) was used as a coding assistant during development and for language editing of the manuscript text.

Geographic definitions

Regions were defined following UN geographic classifications with humanitarian groupings: Horn of Africa (Djibouti, Eritrea, Ethiopia, Kenya, Somalia, South Sudan, Sudan, Uganda); Sahel (Burkina Faso, Chad, Mali, Mauritania, Niger, Senegal); Central Africa (Cameroon, Central African Republic, Democratic Republic of Congo, Republic of Congo); Southern Africa (Malawi, Mozambique, Zambia, Zimbabwe); West Africa (Benin, Côte d'Ivoire, Ghana, Guinea, Liberia, Nigeria, Sierra Leone, Togo); Central America (El Salvador, Guatemala, Haiti, Honduras, Nicaragua); Asia (Afghanistan, Bangladesh, Myanmar, Nepal, Pakistan, Yemen).

Episode detection

Crisis episodes were defined as contiguous periods during which a location remained at IPC Phase 3 (Crisis) or above. We applied forward-fill interpolation to bridge gaps of up to 12 months, reflecting the validity periods of underlying assessments. This threshold was selected based on typical IPC/FEWS NET assessment cycles (3–4 months), allowing up to three consecutive missing assessment periods while maintaining episode continuity. Sensitivity analysis using 6-month and 18-month thresholds showed 4.2% and 2.8% of episodes reclassified respectively, with minimal impact on archetype distributions or recovery ratios (Extended Data Table 3). Gaps exceeding 12 months were treated as episode boundaries.

Left-censored episodes, those beginning in the first observation month for each location, were flagged (141 episodes, 8.5%) but included in the primary analysis, as excluding them would introduce survivorship bias. Sensitivity analysis excluding left-censored episodes yields 1,517 episodes across 41 countries with qualitatively identical findings (Extended Data Table 5).

Our episode detection methodology introduces additional potential biases. By defining episodes as periods at IPC Phase 3 or above, we exclude near-crises peaking at Phase 2, potentially overstating recovery asymmetry if Phase 2 crises show different dynamics. The IPC classifies geographic areas rather than households, and area-level recovery does not guarantee household-level recovery; within-area heterogeneity means some households may remain acutely food insecure even as area classifications improve. While we flagged left-censored episodes (141, 8.5%) and included them in primary analysis with sensitivity analysis confirming qualitatively identical findings when they are excluded, we did not systematically address right-censoring: episodes ongoing at the end of the study period (May 2024) have unknown true durations, potentially underestimating the length of protracted emergencies.

Gap analysis

Recovery gaps were defined as the interval between the end of one crisis episode (return to Phase 2 or below) and the start of the subsequent episode at the same location. Gap compression over time was assessed using both aggregate trends and within-location analysis. To control for potential composition

bias from monitoring expansion, we conducted matched-location analysis restricted to locations with transitions in both early (2011–2015) and late (2020–2023) periods. Escalation was defined as an increase in peak IPC phase between successive episodes (e.g., Phase 3 peak followed by Phase 4 peak). Gap duration categories were defined as: very short (0–3 months), short (4–6 months), medium (7–12 months), long (13–24 months), and very long (>24 months).

Archetype classification

Episodes were classified into eight archetypes using a rule-based decision tree combining three dimensions: Duration class (short <12 months, medium 12–36 months, or protracted >36 months); Severity class (moderate for peak Phase 3, severe for peak Phase 4, or extreme for peak Phase 5); and Volatility class (stable for phase variance <0.1 and ≤1 transition, moderate, or volatile for variance >0.3 or ≥3 transitions).

Classification rules were applied in priority order: (1) severe shock (short, severe/extreme, stable); (2) entrenched moderate (protracted, moderate, stable); (3) protracted emergency (protracted, severe/extreme); (4) oscillating (volatile, with 3 or more transitions); (5) escalating (late peak position, defined as peak occurring in final tercile of episode); (6) rapid onset (early peak position, defined as peak in first tercile); (7) seasonal crises (short, moderate); (8) prolonged moderate (residual).

The classification algorithm was validated through 1,700 test cases, including unit tests, boundary cases, and cross-validation against stored episodes, achieving 100% replicability. Sensitivity analysis varying thresholds by ±10% showed limited impact on classification (1.75–2.83% of episodes affected by duration threshold changes; <0.2% by volatility threshold changes).

Transition analysis

Monthly transition probabilities were calculated from consecutive observations within the interpolated time series[70]. For each phase pair (i, j), we computed $P(i \rightarrow j)$ as the count of transitions from phase i to phase j divided by the total observations at phase i. The recovery ratio was calculated as $P(4 \rightarrow 3) / P(3 \rightarrow 4)$. Confidence intervals were computed using bootstrap resampling (10,000 iterations) at the location level, which accounts for spatial autocorrelation by treating each location's full time series as a single resampling unit. Percentile confidence intervals (2.5th and 97.5th percentiles) were reported.

Recovery degradation was assessed by stratifying transitions by episode duration at the time of observation. We calculated recovery probability (Phase 4 to Phase 3) for episodes in their first 3 months, 7–12 months, 13–24 months, and beyond 24 months.

Temporal comparison

We compared episode characteristics between early (2011–2017) and recent (2018–2023) periods using chi-square tests for categorical variables and Welch's t-tests for continuous variables. Statistical significance was assessed at $\alpha = 0.05$ with Bonferroni correction for multiple comparisons.

Archetype transition visualization

To visualize archetype transitions over time, we assigned each crisis episode to all time periods it overlapped with (not only the period of onset), ensuring that ongoing crises were represented in each period during which they were active. For locations with multiple concurrent episodes in a single period, we retained the most severe archetype. Transition flows between consecutive periods were computed as the count of locations changing from one archetype to another. A cohort-controlled analysis restricted to the 395 locations monitored in 2016 was conducted as a robustness check against monitoring expansion effects.

It is important to note that the findings indicating a “crisis staircase” of food crises progressively worsening through repeated transitions rest on a limited sample completing the full seasonal-to-prolonged-to-protracted pathway (n = 10). However, broader evidence of partial escalation (114 locations) and current entrapment in severe states (14.9% of multi-episode locations) supports the underlying dynamic.

Declarations

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Author Contributions

RJC: Conceptualization, Methodology, Software, Formal Analysis, Investigation, Data Curation, Writing (Original Draft), Visualization. KK: Review & Editing. JMB: Review & Editing. PB: Supervision, Writing, & Editing.

Competing Interests

The authors declare no competing interests.

Data Availability

The Harmonized Food Insecurity Dataset (HFID) version 1.1.1 is available at Zenodo: https://doi.org/10.5281/zenodo.15017473

Code Availability

Analysis code will be made available upon acceptance.

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Tables

Table 1 | Eight archetypes of food security crises.

Based on 1,658 crisis episodes from 49 countries, 2011–2023. Episodes are defined as contiguous periods at IPC Phase 3 or above. IQR = interquartile range.

Archetype	n	%	Median duration (months)	Peak severity	Description
Seasonal crisis	1204	72.6	3	Phase 3	Short, cyclical crises following agricultural calendars
Prolonged moderate	224	13.5	20	Phase 3	Stable Phase 3 conditions for 12–36 months
Protracted emergency	97	5.9	67	Phase 4–5	Multi-year crises at severe/extreme levels
Rapid onset	53	3.2	8	Phase 3–4	Quick escalation to peak, then gradual recovery
Entrenched moderate	38	2.3	52	Phase 3	Persistent Phase 3 beyond 36 months
Oscillating	16	1.0	15	Phase 3–4	Volatile phase changes with ≥3 transitions
Severe shock	19	1.1	4	Phase 4–5	Brief reach to Phase 4/5 with rapid resolution
Escalating	7	0.4	18	Phase 3–4	Progressive worsening trajectory

Table 2 | Differentiated response framework by crisis archetype.

Framework matches response strategies to crisis characteristics based on recovery probability and intervention window analysis.

Archetype	%	Recovery probability	Intervention window	Primary response strategy
Seasonal crisis	73%	High	Predictable (seasonal)	Shock-responsive social protection; forecast-based financing; lean-season cash transfers
Prolonged moderate	~14%	Moderate (degrading)	12–36 months	Multi-year resilience investment; graduation programming; livelihood diversification
Protracted emergency	~6%	Low (<2% after 24mo)	Narrow (first 3 months)	Sustained humanitarian commitment; conflict resolution; political stabilization
Rapid onset	3%	High (initially)	Narrow (weeks)	Surge response capacity; pre-positioned resources; rapid deployment
Entrenched moderate	2%	Very low	Long-term	Structural transformation; development programming; systems change
Oscillating	1%	Variable	Between shocks	Adaptive programming; flexible funding; conflict-sensitive approaches
Severe shock	1%	High	Very narrow	Emergency response; pre-arranged finance; rapid recovery support
Escalating	<1%	Declining	Immediate	Early warning response; scale-up triggers; geographic expansion monitoring

Figures

Main Figures

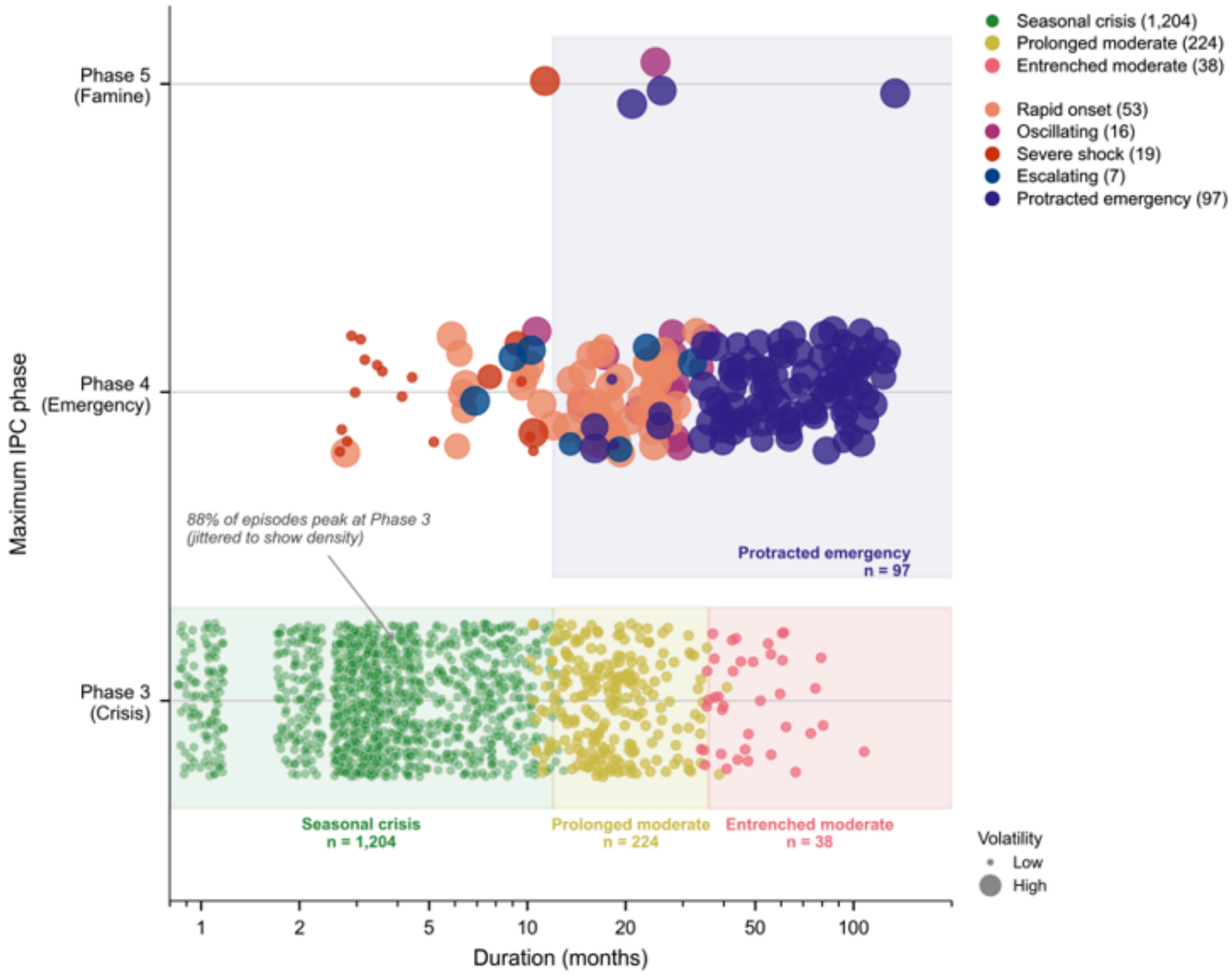


Figure 1

Eight archetypes of food security crises. Scatter plot of 1,658 crisis episodes showing duration (x-axis, log scale) versus mean IPC phase (y-axis), colored by archetype. Seasonal crises (dark blue) cluster at short duration and moderate severity. Protracted emergencies (red) occupy the long-duration, high-severity space. Vertical dashed lines indicate duration thresholds (12 and 36 months); horizontal lines mark Phase 3 and Phase 4 severity boundaries. Marginal histograms show distributions along each axis.

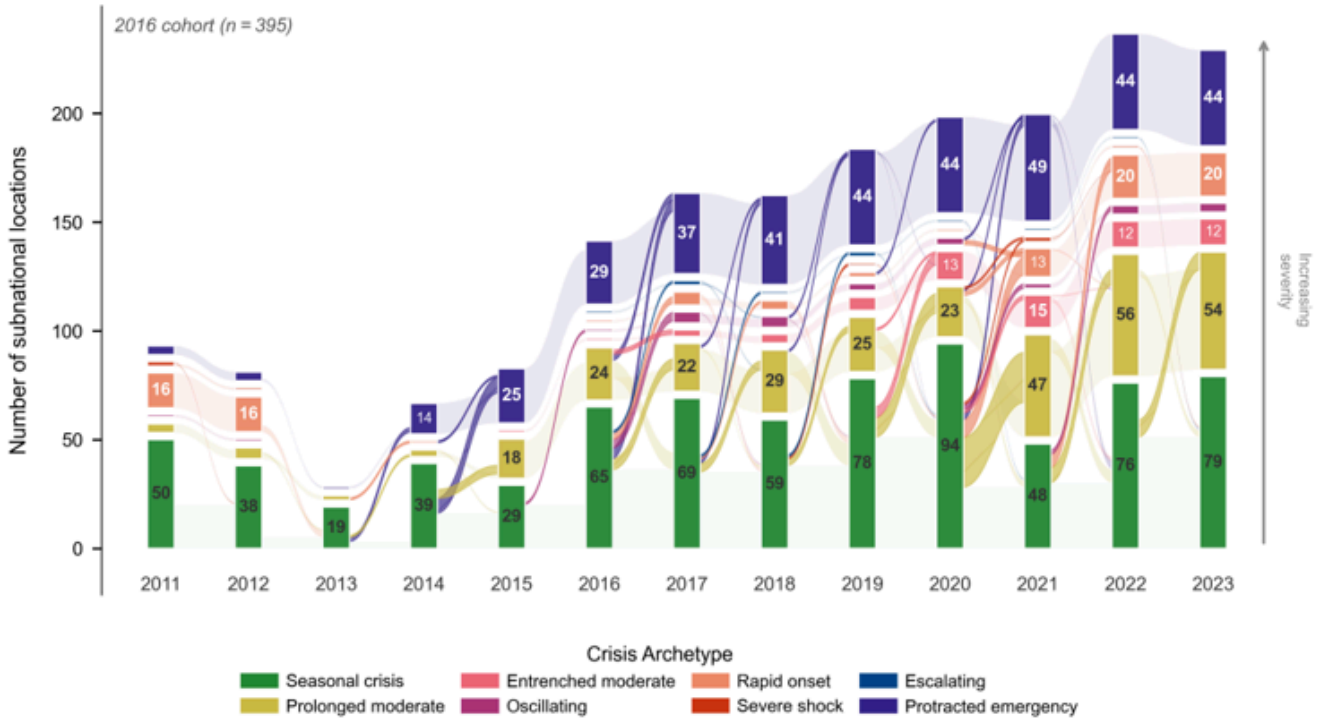


Figure 2

Annual evolution of crisis archetypes (2011–2023). Stacked bars show the number of subnational locations classified under each crisis archetype per year for the 2016 monitoring cohort (n = 395 locations continuously monitored since 2016), controlling for the expansion of monitoring coverage over time. Flows between bars show individual locations transitioning between archetypes. Bold hatched flows highlight escalation transitions (increasing severity); faint flows indicate persistence within the same archetype; intermediate flows indicate recovery (de-escalation). Each location is assigned its most severe concurrent archetype per year. Archetypes are stacked from seasonal crises (bottom) to protracted emergency (top), with severity increasing upward. Within this fixed cohort, protracted emergencies grew from 4 locations in 2011 to 44 by 2022, an 11-fold increase, while seasonal crisis counts remained relatively stable, illustrating a structural shift toward more severe and persistent crises.

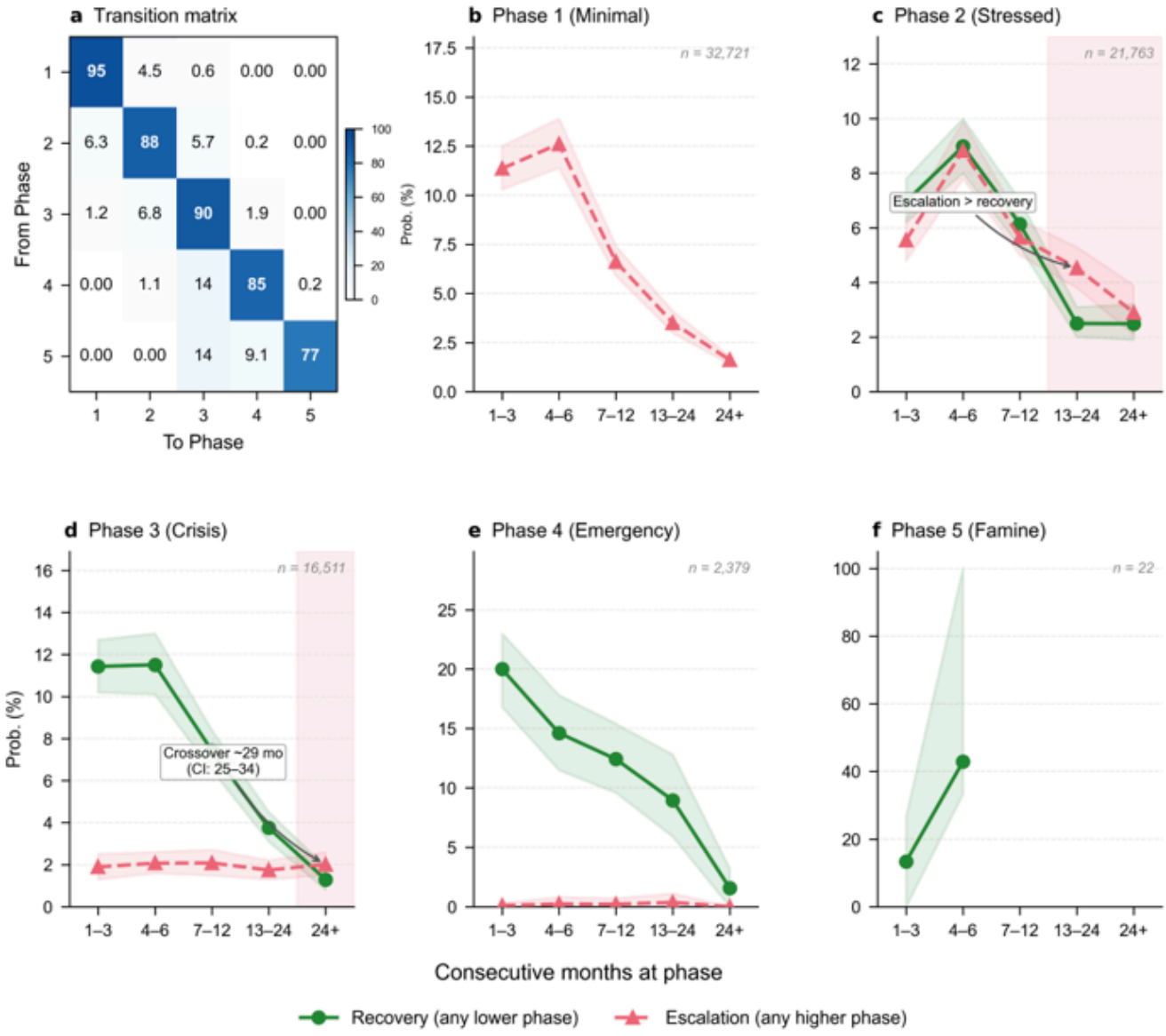


Figure 3

Phase transition dynamics across all IPC phases. (a) Monthly transition probability matrix showing the probability of moving from one IPC phase (row) to another (column). Diagonal values (bold) represent the probability of remaining at the same phase. (b–f) Duration-conditioned recovery and escalation probabilities for IPC Phases 1–5. Recovery (green, solid) is defined as any downward transition; escalation (red, dashed) as any upward transition. Shaded bands show 95% bootstrap confidence intervals (10,000 iterations, location-level resampling). X-axis bins represent consecutive months at a given phase; sample sizes are shown per panel. (b) Phase 1 (Minimal): escalation risk declines from 11.4% to 1.6% as duration increases. (c) Phase 2 (Stressed): recovery and escalation are roughly balanced (7–9%), both declining with duration. (d) Phase 3 (Crisis): recovery decays from 11.4% to 1.3%, crossing below escalation at approximately 29 months (CI: 25–34), after which escalation exceeds recovery — the "trap state" threshold. (e) Phase 4 (Emergency): recovery decays steeply from 20.0% to 1.6%. (f) Phase 5 (Famine): only 22 transitions observed across two duration bins; wide confidence

intervals reflect limited data. Data source: HFID v1.1.1 (n = 311,838 location-months, 745 admin1 locations, 2007–2024). Pipeline: FEWS NET priority, MAX aggregation, 12-month interpolation gap.

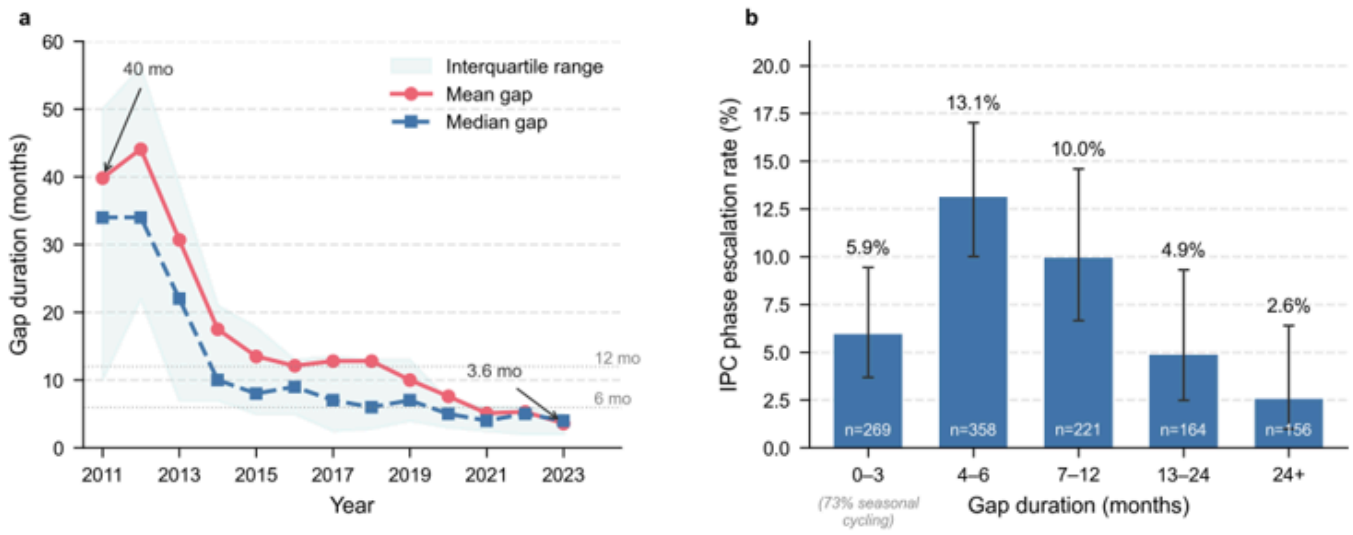


Figure 4

Recovery gap compression and escalation risk. (a) Mean gap duration between successive crisis episodes at the same location, showing compression from 40 months (2011) to 3.6 months (2023). Red line shows mean gap; blue dashed line shows median; shaded area indicates interquartile range. Dotted reference lines mark 6-month and 12-month thresholds. Analysis includes 1,168 transitions across 284 locations. (b) IPC phase escalation rate by gap duration category. The 4–6 month category shows highest escalation risk (13.1%), representing a pivotal vulnerability period for crisis transformation. Very short gaps (0–3 months) show lower escalation because 73% are same-archetype transitions (seasonal cycling). Error bars indicate 95% Wilson confidence intervals.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- ExtendedData.docx