IFPRI Discussion Paper 02353

September 2025

On the Points of Failure and Entry in Global Food Systems

John M. Ulimwengu

Development Strategies and Governance Unit

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE

The International Food Policy Research Institute (IFPRI), a CGIAR Research Center established in 1975, provides research-based policy solutions to sustainably reduce poverty and end hunger and malnutrition. IFPRI's strategic research aims to foster a climate-resilient and sustainable food supply; promote healthy diets and nutrition for all; build inclusive and efficient markets, trade systems, and food industries; transform agricultural and rural economies; and strengthen institutions and governance. Gender is integrated in all the Institute's work. Partnerships, communications, capacity strengthening, and data and knowledge management are essential components to translate IFPRI's research from action to impact. The Institute's regional and country programs play a critical role in responding to demand for food policy research and in delivering holistic support for country-led development. IFPRI collaborates with partners around the world.

AUTHORS

John M. Ulimwengu (j.ulimwengu@cgiar.org) is a Senior Research Fellow in the Development Strategies and Governance (DSG) Unit of the International Food Policy Research Institute (IFPRI), Washington, DC.

Abstract

This study develops a dual-framework for identifying points of failure (PFs) and points of entry (PEs) in global food systems. Building on Schneider et al. (2025), we extend their entry-point analysis by introducing PFs—nodes where systemic risk concentrates. Using dynamic systems modeling and directed network analysis of 50 indicators from the Food Systems Countdown Initiative, we derive PF and PE indexes based on structural metrics from the adjacency matrix. While empirically grounded in network topology, the model accommodates behavioral lags and policy sensitivity. Findings reveal that high-risk and high-leverage components often overlap, enabling more strategic and adaptive interventions. Designing interventions without understanding fragility would be akin to engineering a machine for acceleration while ignoring its weakest links.

Keywords: Systems, food, dynamics, network, failure, entry

Acknowledgments

We gratefully acknowledge the Food Systems Countdown Initiative (FSCI) team for providing access to data, publications, and valuable insights that greatly informed this research.

Introduction

With more than 700 million people experiencing hunger and malnutrition, and food production systems exerting unsustainable pressure on natural resources, achieving food systems sustainability by 2030 is one of the world's most urgent goals. However, conventional approaches to food systems reform often treat problems such as dietary quality, environmental degradation, and governance shortcomings in isolation. This reductionist perspective overlooks the reality that food systems function as complex adaptive networks, characterized by feedback loops, nonlinear dynamics, and deeply nested interdependencies (Ostrom, 2009).

This study addresses the need for a systems-based framework capable of diagnosing structural fragility and identifying strategic leverage points for transformation. The purpose of this paper is to introduce a novel methodology for identifying critical components of global food systems—termed points of failure (PFs) and points of entry (PEs)—that either amplify systemic risk or offer disproportionate potential for impactful interventions. Using directed network analysis derived from the Food Systems Countdown Initiative (FSCI), we map the relationships among over 50 global food systems indicators and apply graph-theoretic metrics to evaluate each component's vulnerability and influence.

This research builds directly on the foundational work of Schneider et al. (2025), who developed the FSCI indicator network and identified governance and resilience as central entry points for systemic transformation. Their study provided a conceptual and expert-informed mapping of causal relationships across food systems indicators, highlighting the role of governance in shaping nutritional, environmental, and equity outcomes. This paper extends that framework by offering a quantitative, replicable method to evaluate system-wide fragility and leverage using network science and dynamic systems modeling. In this sense, it serves as both a continuation and operationalization of Schneider et al.'s insights, translating their structural theory into actionable metrics for strategic intervention.

What sets this research apart is its integration of empirically grounded network data with a dynamic systems model that accounts for behavioral responses, policy lags, and nonlinear feedback loops. While previous studies have highlighted the complexity of food systems in qualitative terms (Meadows, 1999; Willett et al., 2019), this paper advances the field by offering a quantitative approach to fragility and leverage. It identifies not just where interventions are needed, but where they can be most effective—in other words, those nodes[1] where a modest policy shift can realign system behavior, or where failure to act may allow systemic divergence.

At the heart of our modeling framework are three interconnected forces that shape food systems evolution: (1) intrinsic dynamics of each component, (2) inter-component influences

[1] In this paper, components and nodes are used interchangeably.

encoded in a directed adjacency matrix, and (3) policy feedback signals that attempt to realign components with sustainability goals. These forces are captured through coupled nonlinear differential equations, allowing for the inclusion of behavioral time lags and contextual factors such as institutional readiness or market access.

The identification of PFs focuses on components that are structurally fragile—those with high in-degree centrality, nonlinear sensitivity, and weak policy responsiveness. Such nodes absorb disturbances from multiple upstream sources and can become epicenters of systemic breakdown. For instance, indicators like *prevalence of undernourishment* or *cost of a healthy diet* are influenced by diverse variables, from trade and pricing to environmental stressors and governance quality. During the 2007–2008 global food crisis, modest commodity price increases rapidly cascaded through food systems, leading to widespread hunger and social unrest (Headey & Fan, 2008).

In contrast, PEs are components that hold outsized systemic influence. These include nodes with high out-degree centrality, high policy sensitivity, and proximity to many other nodes in the network. Governance-related indicators such as *civil society participation* and *government effectiveness* emerge as prime entry points because they influence multiple downstream outcomes. When interventions are applied through these nodes, the resulting impact propagates widely, thereby affecting dietary diversity, environmental management, and social equity (Schneider et al., 2025).

This dual framework of fragility and leverage provides a powerful decision-support tool for policymakers. High-PF nodes signal where stability must be reinforced through protective policies like cash transfers, social safety nets, or coordinated subsidies. High-PE nodes indicate where strategic, well-timed interventions can produce ripple effects across the system. Importantly, some components may fall into both categories, given their propensity for both vulnerability and influence. Although these dual-node roles present unique opportunities for transformation, they must be managed carefully to avoid unintended consequences.

Ultimately, this paper makes the case that food systems transformation requires more than isolated reforms—it demands a strategic understanding of system structure, behavior, and leverage. By identifying where the system is most fragile and most responsive, this approach enables the design of policies that are adaptive, coherent, and capable of navigating the complexity of a rapidly changing world.

Modelling food systems transformation

Schneider et al. (2025) presented a groundbreaking systems framework that mapped the interdependencies among 50 global food systems indicators using expert-elicited causal relationships. Their work identified PEs—nodes such as government effectiveness, civil society

participation, and the right to food—as high-leverage components that could be strategically targeted to influence broad systemic change. However, while their analysis provided conceptual insight into leverage, it did not formally define or diagnose PFs—that is, nodes where systemic fragility accumulates and from which cascading disruption may emerge. This paper builds directly upon Schneider et al.'s foundation, offering a dual analytical framework that identifies both PEs and PFs through a dynamic modeling lens.

Our theoretical model is based on coupled nonlinear differential equations that integrate self-dynamics, network interactions, and policy feedback to allow for the inclusion of both adjacency-based and non-adjacency-based characteristics such as behavioral delays, policy responsiveness, and system sensitivity. While the empirical implementation in this study focuses on metrics derived solely from the adjacency matrix A (for example, in-degree, out-degree, centrality, clustering), the theoretical framework is more expansive: it accounts for dynamic properties such as the sensitivity of each component's intrinsic growth, nonlinear interaction effects, and responsiveness to delayed or conflicting policy signals. By formalizing these mechanisms, we provide a rigorous foundation for understanding not just where food systems are most malleable to intervention, but also where they are most vulnerable to failure. This dual structure enables a more precise and adaptive approach to food systems transformation—one that identifies not only strategic levers but also structural fault lines.

Food systems transformation modeling can be represented by a set of coupled nonlinear differential equations that describe how each system component evolves over time. The canonical form of this model is:

$$\frac{dx_i}{dt} = F(x_i) + \sum_{i=1}^{N} A_{ij} G\left(x_i, x_j\right) + \phi_i(S_i)$$

This expression integrates three fundamental forces that govern the trajectory of any food systems indicator x_i: self-dynamics, interactions, and policy feedback. Each component follows its own intrinsic behavior, independent of external pressures. For example, crop yields might naturally increase over time due to incremental improvements in farming practices, modeled as:

$$F(x_i) = r_i \left(1 - \frac{x_i}{K_i}\right) x_i$$

This is a logistic growth function, where r_i is the growth rate and K_i the carrying capacity.[2] It captures a key food systems property in the form of bounded growth. Such models have been

[2] Traditionally, in population ecology, carrying capacity (K) represents the point at which a species' population growth stabilizes due to limiting factors such as food availability, water, space, or competition. When a population exceeds this threshold, it triggers a range of negative feedback—resource depletion, habitat degradation, and population decline—until a new equilibrium is reached (Odum, 1983).

widely used in agricultural and ecological modeling to represent natural resource constraints (see, for example, Godfray et al., 2010).

No component operates in isolation. As in Schneider et al. (2025), the adjacency matrix A encodes expert knowledge about which indicators influence each other. The function $G(x_i, x_j)$ quantifies the magnitude and direction of that influence—it could be linear, saturating, or threshold-based, depending on the nature of the relationship. For instance, an increase in agricultural land might raise the availability fruits and vegetables, but it might also decrease biodiversity or water quality.

These interactions introduce complex feedback loops, and their structure plays a critical role in system stability and resilience. If a node or component receives influence from many others (that is, high in-degree), it becomes structurally fragile, meaning that any change elsewhere cascades through it. This aligns with concepts in network science and systems ecology (May, 1972; Scheffer et al., 2012).

The third term represents human agency, capturing signals such as subsidies, taxes, education campaigns, or legal reforms. These are applied to push a component toward a desired target x_i^*.

While policy signals may be designed and triggered in real time, their effects on human behavior and systemic outcomes are never instantaneous. In complex systems, the path from intervention to impact is often mediated by delays, whether structural, behavioral, institutional, or cultural. To capture this temporal lag in food systems modeling, we introduce a behavioral response function:

$$B_{i,t} = g(S_{i,t-\tau_i}, C_i)$$

This function indicates that food systems actors respond to signals based on past inputs, filtered through the lens of their context:

- $B_{i,t}$ represents the behavioral output or action at time t that influences the evolution of component x_i. This could be farmer adoption of a new practice, consumer dietary change, or institutional implementation of a regulation.
- $S_{i,t-\tau_i}$ is the policy signal issued at an earlier time $t - \tau_i$, where τ_i is the response delay.
- C_i encompasses contextual factors that shape how signals are interpreted and acted upon. This includes institutional readiness, trust in governance, infrastructure and market access, and social norms and preferences.

The behavioral signal $B_{i,t}$ then feeds into the system's evolution via the policy influence function $\phi_i(S_i)$, such that:

$$\phi_i\ (S_i)\ =\ h(B_{i,t};\beta_i)$$

—where *h(·)* can be linear or nonlinear depending on institutional responsiveness. This layered structure allows the model to incorporate lags and context-dependent behavior in how policy affects each node.

This dynamic model of food systems transformation reveals a critical and often underappreciated insight: interdependence and fragility amplify systemic risk. Food systems are not collections of isolated variables. Rather, they are densely interconnected networks in which behavior and outcomes propagate through multiple feedback loops. Within such a system, the structural and behavioral characteristics of individual components determine their vulnerability to shocks and their potential as leverage points. When viewed through the lens of systems dynamics, it becomes clear that some nodes—those with high centrality, sensitivity to disturbance, or exposure to contradictory signals—can act as either stabilizers or amplifiers depending on the nature of the perturbation.

Consider a component that holds high centrality in the system. In network terms, this means it has many incoming or outgoing connections, suggesting that it is either influenced by or exerts influence on numerous other components. For example, food affordability is influenced by prices, income, agricultural yield, and trade access, but also shapes dietary quality, malnutrition rates, and labor force productivity. If such a node is perturbed—whether by a climate shock, conflict, or policy misalignment—the resulting impact is not contained; it cascades.

Beyond structural centrality, sensitivity to change—a property encoded in the self-dynamic parameters of the model—further exacerbates systemic fragility. A component with unstable or poorly dampened dynamics (for example, rapid swings in GHG emissions or market prices) tends to amplify disturbances rather than absorb them. For instance, if livestock emissions respond strongly to shifts in feed prices or consumer demand, a minor change in upstream variables can lead to disproportionate impacts on emissions trajectories. This introduces volatility into the system and reduces its capacity to maintain trajectory toward sustainability targets.

A third source of fragility arises when nodes receive conflicting policy signals. In complex governance environments, it is not uncommon for a single subsystem—like agricultural land use—to be subject to simultaneous but contradictory pressures; one policy may subsidize fertilizer use to boost yields, while another attempts to reduce runoff and protect waterways. These opposing signals interfere with behavioral adaptation, creating policy noise that undermines system coherence. Over time, this noise can lead to policy fatigue or unintended consequences, as actors—be they farmers, consumers, or governments—struggle to interpret shifting incentives (Vermeulen et al., 2020).

Yet, it is precisely this interdependent structure that offers a powerful opportunity: the ability to leverage transformation through targeted, well-timed interventions. The dynamic framework provided here shows that policy signals $S_i(t)$, when correctly aligned with system sensitivities and deployed through strategically important nodes, can realign behaviors and outcomes even in the presence of shocks. For example, a subsidy that reduces the cost of diverse, nutrient-rich foods can simultaneously reduce undernutrition, improve dietary diversity, and lower demand for resource-intensive commodities—all with compounding effects across the system (Springmann et al., 2018).

Moreover, because the model accounts for feedback and time lag, it enables the design of adaptive policies—interventions that are not static but evolve in intensity and direction as the system responds. This approach aligns with recent thinking in food systems governance, where resilience is no longer defined as resistance to change, but as the capacity to absorb shocks and reorganize while maintaining function (Tendall et al., 2015). In such a context, identifying entry points is both a matter of centrality and importance, and of dynamic leverage where a relatively small, feasible policy adjustment can tip the system back toward its target trajectory.

In essence, our framework underscores that food systems fragility and leverage are two sides of the same coin. Components that pose the greatest risk of divergence under perturbation are often the same that, when engaged strategically, offer the highest potential for transformation. Understanding where these pivot points lie, and how they respond to signal intensity and timing, is essential for designing policies that are not only impactful but also resilient and adaptive in the face of a changing world.

PFs are system components (nodes) that, if destabilized, amplify divergence from the desired trajectory , increasing systemic risk. They are characterized by**:**

- High in-degree centrality in A: Components highly influenced by others (, large $\sum_j A_{ij}$) tend to propagate failures. These nodes absorb upstream shocks and magnify downstream effects.
- Unstable or weakly damped dynamics in $F(x_i)$: Examine the derivative $\frac{\partial F}{\partial x_i}$. If it's highly sensitive or exhibits nonlinearity prone to overshoot (e.g., logistic with high r_i), the system may diverge quickly from equilibrium.
- Amplification in interactions $G(x_i, x_j)$: Nonlinear or threshold-based G can cause tipping points. If a small perturbation in x_j causes a large change in x_i, that indicates fragile coupling.
- Low policy sensitivity ($\beta_i \to 0$): If a component resists correction via policy (low $\phi_i(S_i) = \beta_i$), it becomes a policy-resistant risk node.

PEs are nodes where modest, well-timed interventions lead to outsized system improvements and cost-efficient realignment. They are recognized by:

- High out-degree centrality in A : Nodes with high influence (large $\sum_i A_{ij}$) are effective levers. Change in x_i ripples outward to many x_j, making interventions impactful.
- High policy sensitivity $(\beta_i \gg 0)$: Nodes that respond strongly to policy are ideal targets. Modest S_i yields strong shifts in x_i.
- Behavioral responsiveness (large $\frac{\partial B_{i,t}}{\partial S_{i,t-\tau}}$): Nodes with short delays τ and favorable context C_i offer fast returns on intervention.
- Systemic leverage (feedback loops): Identify feedback cycles that dampen instability when this node is positively perturbed.

In this paper, the empirical implementation uses only metrics[3] derived from the adjacency matrix A as reported in Table 1.

[3] See Annex A for related formulas

Table 1: Network metrics for critical food systems points

Property	Use for PF or PE	How to derive from A
In-Degree	PF	Nodes with high in-degree are receivers of many influences → structurally fragile.
Out-Degree	PE	Nodes with high out-degree are senders of influence → structurally powerful levers.
Centrality metrics	Both	Compute eigenvector centrality, betweenness, closeness to find structurally important nodes.
Hub/Authority scores	PF (hubs), PE (authorities)	Helps identify influential nodes in directed networks.
Clustering coefficient	PF	Nodes in tightly interlinked subnetworks can amplify local shocks.
Feedback loops / cycles	PF	Presence of directed cycles can indicate potential for amplification or instability under feedback.
Network motifs	PE	Identify leverage-prone substructures like feedforward loops or bottlenecks.
Strongly connected components	PF	Nodes in dense subnetworks may trap disturbances.
Shortest path lengths	PE	Nodes close to many others can transmit influence efficiently.

Data

The data used in this paper are from the network analysis presented in Schneider et al. (2025) originates from the Food Systems Countdown Initiative (FSCI), a global framework for tracking progress toward sustainable food systems by 2030. The dataset includes cross-national observations from 2000 to 2022, with complete panel data available for 94 countries that have sufficient time–series coverage. The FSCI was designed to support cross-country comparison and policy tracking, and its metrics were harmonized using protocols from international agencies including FAO, WHO, World Bank, and UNICEF (Fanzo et al., 2022; Vervoort et al., 2023).

This framework comprises a curated set of 50 indicators that span five interdependent dimensions: diets, nutrition and health; environment and natural resources; livelihoods and equity; governance; and resilience. These indicators serve as standardized proxies for

monitoring the structural, social, economic, and ecological health of food systems across multiple countries.

The adjacency matrix used in this study was developed by the FSCI team through an expert elicitation process involving over 30 scholars and practitioners. These experts represented a wide range of domains critical to food systems transformation, including food policy, epidemiology, environmental science, agricultural economics, governance, and systems modeling. Their affiliations included international organizations (for example, FAO, WHO, IFPRI), universities, and national research institutes across six continents. Structured elicitation workshops, peer review of linkages, and consensus scoring were used to finalize the directed connections between indicators (Herforth et al., 2022).

Thematic working groups, each focused on a particular domain of the FSCI framework, assessed every possible pairwise combination of indicators to identify directional influences. For each pair, the experts determined whether a direct causal link existed, what the direction of influence was, and how strong the relationship was based on theory, empirical evidence, or policy experience. These assessments were encoded into a directed adjacency matrix, with each cell representing a perceived causal influence from one indicator to another. If an expert group determined that indicator *X* influences indicator *Y*, this directional relationship was recorded as a non-zero entry in the matrix cell corresponding to *Y* receiving influence from *X*. The resulting matrix thus captures not only the presence of linkages but also the system's directional structure of influence.

This adjacency matrix served as the basis for the network graph, captured in Figure 1. The graph reveals a highly connected system, with some indicators emerging as structurally central and others more peripheral. Unlike typical statistical correlations, this network is built on informed, theory-backed judgments of causality, offering a conceptual model of how changes in one part of the food system may cascade to others.

The significance of this network structure lies in its utility for identifying two classes of critical system components: PFs and PEs. PFs, which are influenced by a large number of other indicators, are nodes with high in-degree centrality. Their fragility lies in the fact that perturbations elsewhere in the system accumulate and converge upon them. Such nodes often represent outcome variables, such as the prevalence of undernourishment or the cost of a healthy diet. These are not only affected by multiple upstream factors but are also tightly coupled with social and economic stressors. When these nodes become destabilized, the resulting divergence propagates outward, exacerbating system-wide costs and potentially overwhelming policy interventions.

In contrast, PEs are characterized by high out-degree centrality, betweenness, and systemic influence. These nodes, such as governance quality, civil society participation, or the right to food, serve as leverage points from which influence can be projected across the system. Modest interventions at these points can have disproportionate effects due to their position in the network. By realigning behaviors and systemic trajectories through such nodes, policymakers can achieve broader outcomes more efficiently and with lower implementation strain.

Critically, the identification of PFs and PEs is not merely an academic exercise but a practical tool for strategic planning. The network's structure reveals that food systems are not linear or compartmentalized; rather, they function as complex adaptive systems with deeply nested interdependencies. Recognizing this interconnectivity is essential for crafting policy interventions that are robust, adaptive, and capable of producing coherent outcomes across multiple dimensions. Moreover, the network analysis reinforces the view that governance is not just a contextual factor but a structural lever—well-designed governance reforms have the capacity to influence numerous downstream indicators, making them prime candidates for entry-point interventions.

To construct the composite PF and PE indexes, we used normalized scores from multiple network metrics derived from the directed adjacency matrix. The PF index was calculated as the unweighted average of in-degree, clustering coefficient, hub score, and participation in cycles. The PE index was based on out-degree, authority score, eigenvector centrality, betweenness centrality, and shortest path proximity. Each metric was scaled between 0 and 1 prior to aggregation. Indicators scoring above the mean in either index were classified accordingly in the typology.

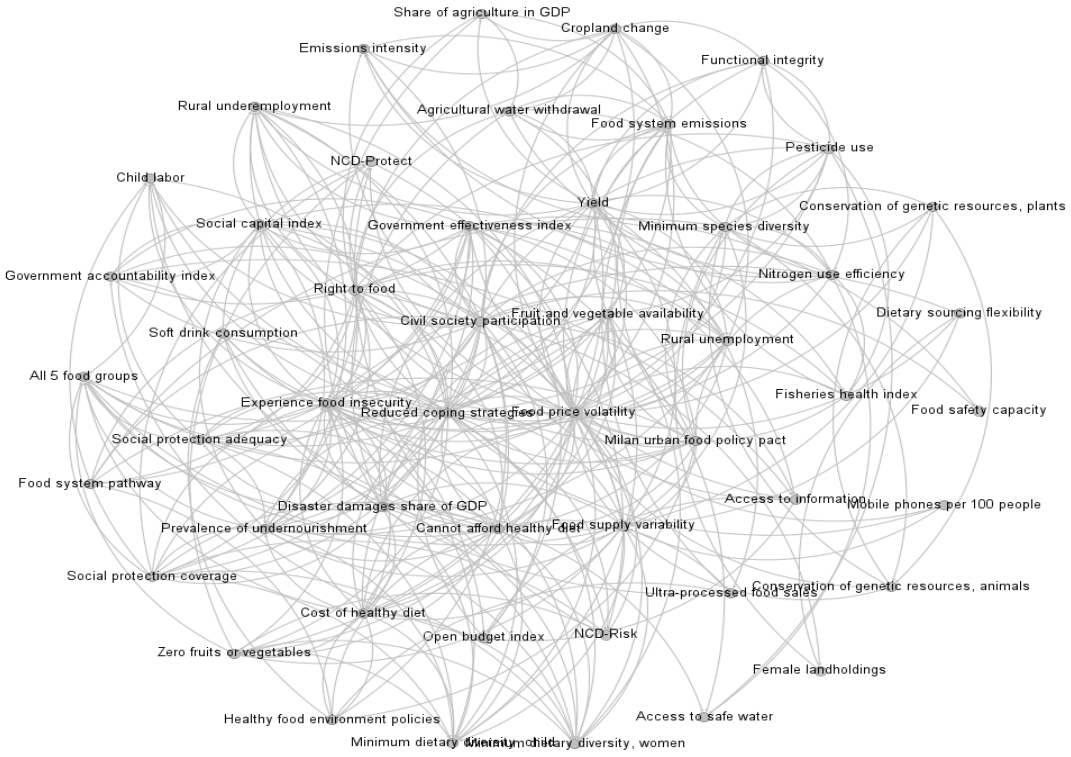
In analyzing Figure 1, a few critical observations emerge. First, the network exhibits high connectivity, affirming that food systems operate not as linear supply chains or siloed sectors but as tightly coupled, complex adaptive systems. Centrality measures help reveal the architecture of influence: indicators such as *civil society participation, government effectiveness*, and *right to food* are positioned as hubs from which influence radiates across the system. Intervening at these nodes—by strengthening governance quality or institutional participation—can produce ripple effects that shape outcomes in nutrition, environmental protection, and socioeconomic equity. This insight aligns with well-established systems theory, which emphasizes the value of targeting high-leverage points to induce wide-reaching systemic change (Meadows, 1999; Ostrom, 2009).

Conversely, certain nodes function as sinks of influence. Indicators[4] such as *prevalence of undernourishment, experience of food insecurity,* and *cost of a healthy diet* have high in-degree

[4] Definitions of all indicators and network metrics are provided at https://www.foodcountdown.org/indicator-architecture

centrality. They are sensitive endpoints shaped by multiple upstream variables. Their position in the network makes them vulnerable to systemic shocks and stresses. Destabilization in any of their influencing indicators—such as agricultural productivity, income inequality, or food price volatility—can cause these outcomes to deteriorate rapidly. Thus, these nodes require special attention not simply because they are indicators of distress but because they reflect systemic fragility. As past events like the 2007–2008 global food crisis and the COVID-19 pandemic have demonstrated, such points of failure can have cascading effects that amplify social and political unrest (Headey & Fan, 2008; Laborde et al., 2020).

Figure 1: Food systems as a network



Source: Author, data from https://www.foodcountdown.org/

Another key dimension highlighted by Figure 1 is the presence of feedback loops. Several indicators exhibit bidirectional or cyclical influences, which are characteristic of systems with nonlinear behavior. For example, a loop involving *experience of food insecurity, coping strategies,* and *social protection coverage* suggests the risk of feedback spirals where initial shocks compound themselves. Such loops also represent intervention opportunities; if positive feedback can entrench disadvantage, then well-designed interventions might stabilize or reverse

harmful cycles. Identifying and targeting nodes embedded in such loops can be critical for achieving durable, adaptive change.

The peripheral but connected placement of environmental indicators like *pesticide use, functional integrity,* and *conservation of genetic resources* reinforces the point that sustainability concerns are not isolated—they are integrated into the systemic behavior of food systems. These nodes link ecological processes to social outcomes, demonstrating that degradation in one domain can erode resilience in another. As highlighted in the EAT–Lancet Commission, integrating environmental boundaries into food systems design is not optional—it is foundational (Willett et al., 2019).

Discussion of the results

Figure 2 presents the ranking of food systems indicators by their PE composite score, a synthetic index designed to identify nodes in the system where targeted interventions could produce system-wide leverage. These composite scores are constructed using structural network metrics—specifically, out-degree centrality, PageRank[5], betweenness centrality, and inverse average path length—all normalized and equally weighted to assess the potential influence of each indicator across the system.

The results provide a strikingly complement—and in some cases, a noteworthy contrast—to the qualitative findings reported in Schneider et al. (2025). There, the authors emphasize governance-related indicators such as *government effectiveness*, *civil society participation*, and *right to food* as foundational levers for transformation. Their network model is rooted in expert elicitation and conceptual systems analysis, which highlight governance as an integrative and amplifying domain that can influence a wide range of downstream outcomes, including food security, dietary diversity, and environmental sustainability.

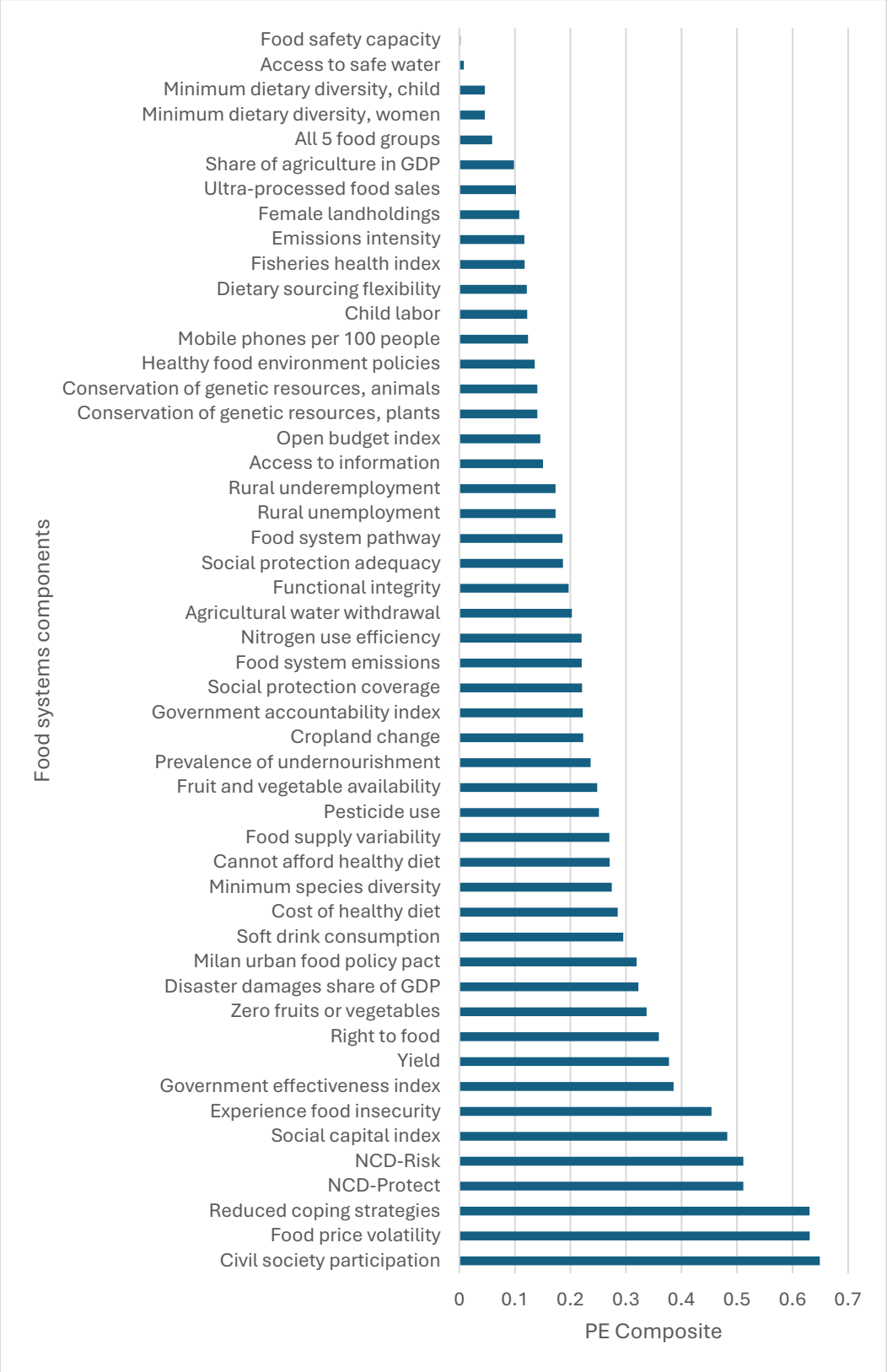
The empirical validation of Figure 2 is especially compelling because it supports some, but not all, of those claims. *Civil society participation* ranks highest on the PE composite index, reinforcing the argument in Schneider et al. (2025) that governance mechanisms are central nodes in a food system's structure of influence. Similarly, *reduced coping strategies*, *open budget index*, and *government effectiveness* all appear prominently, aligning with the paper's emphasis on transparency, accountability, and institutional capacity as critical leverage points.

However, our findings also introduce subtle but important divergences. Indicators such as *experience of food insecurity* and *zero fruits or vegetables* emerge with relatively high PE scores, despite not being emphasized as key entry points in the Schneider et al. (2025) framework.

[5] PageRank is an algorithm developed by Google founders Larry Page and Sergey Brin that ranks web pages in search engine results based on their importance. It operates by counting the number and quality of links to a page, under the assumption that more important pages are likely to receive more links from other websites.

These indicators typically function as outcome variables in policy discourse, but their structural position in the network suggests they may also serve as mediators or amplifiers of systemic change. Their prominence in the PE composite ranking implies that interventions targeting behavioral or consumption-level practices may have broader system effects than previously acknowledged.

Figure 2: Ranking points of entry (PEs)



Source: Author

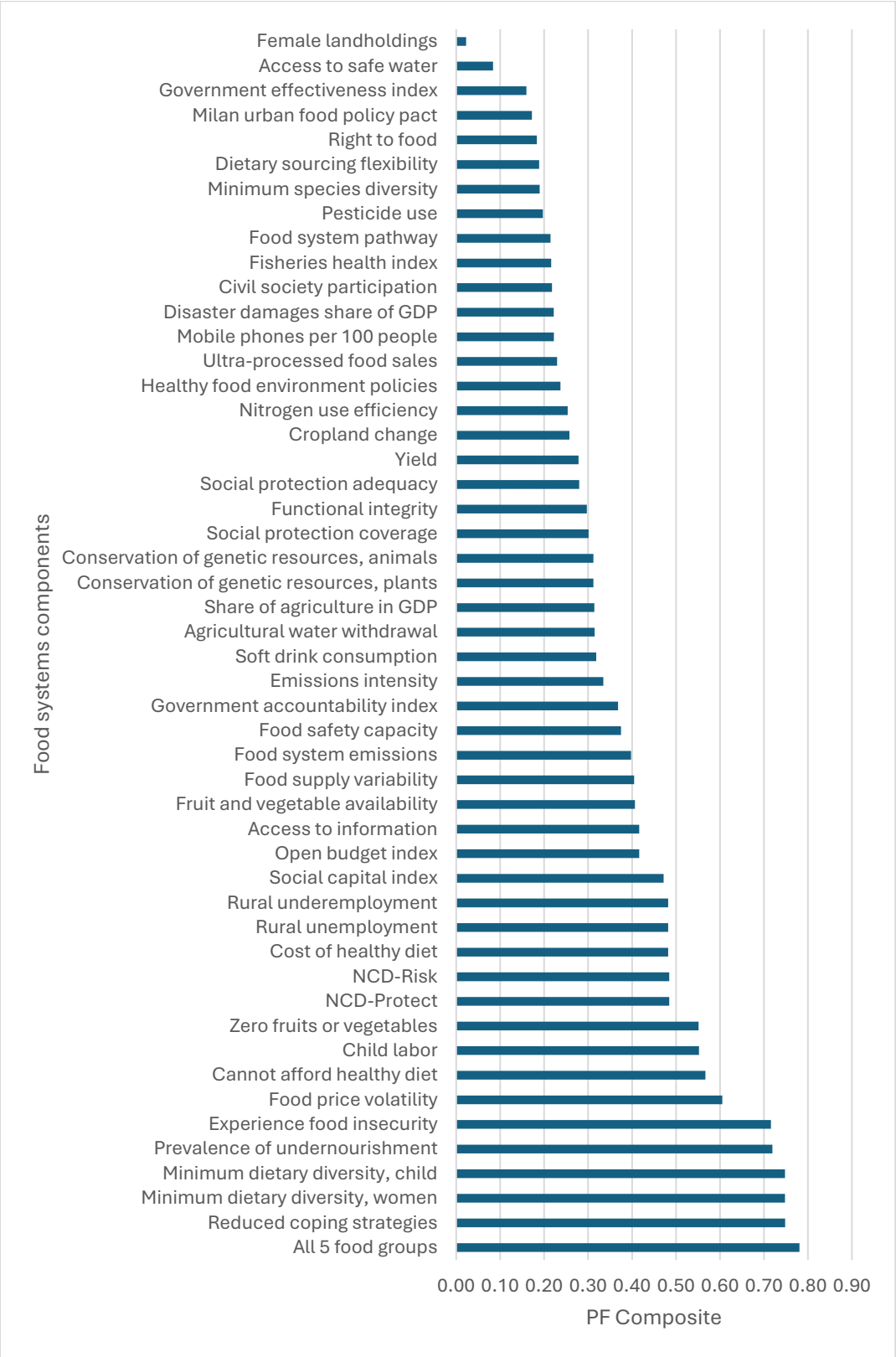
Conversely, certain environmental and production-related indicators—such as *pesticide use*, *minimum species diversity*, and *functional integrity*—score much lower on the PE index. This is consistent with Schneider et al.'s (2025) assertion that while environmental indicators are vital for long-term sustainability, they may not function effectively as immediate levers for rapid transformation unless coupled with governance and behavioral mechanisms. In other words, these indicators are more likely to reflect systemic outcomes rather than drive them, at least within short-to-medium policy cycles.

Another interesting observation is the relatively lower position of *food safety capacity* and *child labor*, which are often cited in development discourse but appear to exert limited systemic influence in structural network terms. This suggests that while such indicators are morally and developmentally critical, their strategic role as entry points for transformation may be limited unless embedded in broader governance or economic reform initiatives.

In essence, our findings operationalize and expand the conceptual findings of Schneider et al. (2025) by using network metrics to assess the actual influence potential of each node. This validates their central thesis—that governance and resilience are pivotal—but it also refines the conversation by offering a measurable hierarchy of influence. This creates a bridge between qualitative systems thinking and quantitative prioritization, offering a practical roadmap for policymakers seeking to intervene efficiently within complex and highly interdependent food systems.

Figure 3 ranks food system indicators by their PF composite score. The PF index aggregates normalized values of key vulnerability-related graph measures—in-degree centrality, eigenvector centrality, and clustering coefficient—each of which captures an aspect of how exposed and structurally fragile a node is within the broader food system. Indicators with high PF scores are those that are most likely to absorb systemic shocks, act as convergence points for upstream risks, and contribute to system-wide instability if left unmanaged.

Figure 3: Ranking points of failure (PFs)



Source: Author

Figure 3 reveals several critical insights into system fragility that align with, yet also extend, the findings of Schneider et al. (2025). In their study, the authors highlight the prevalence of undernourishment, cost of healthy diets, and food insecurity as deeply embedded outcomes influenced by a wide range of drivers. Figure 3 quantitatively reinforces these findings. Indicators such as *prevalence of undernourishment*, *minimum dietary diversity, women*, and *cannot afford healthy diet* all rank among the highest PF scores. Their structural positions—characterized by high in-degree centrality and connectivity to other core domains—demonstrate that these are not merely statistical outcomes, but fragile endpoints in the system. They are particularly sensitive to perturbations in governance, pricing, environmental stressors, and social protection, making them highly responsive yet systemically volatile.

Notably, indicators such as *all 5 food groups* and *reduced coping strategies* also appear at the top of the fragility ranking. These reflect dimensions of dietary adequacy and household resilience, suggesting that food and nutritional security are not only influenced by production or price dynamics but are intricately tied to behavioral and institutional capacity. The high PF scores of these indicators suggest that if nutritional diversity and coping capacity collapse—through, for example, loss of income, supply chain disruption, or policy incoherence—the impacts could reverberate across the entire food system.

An important observation lies in the middle band of the PF rankings, where indicators such as *cost of healthy diet*, *rural underemployment*, *NCD risk*, and *fruit and vegetable availability* occupy structurally significant but less extreme positions. These indicators often function both as influenced outcomes and as intermediaries, linking multiple subsystems. Their placement suggests that while they are not the most fragile nodes, their stability is essential for system buffering and transition. They may not be immediate failure points, but their degradation can initiate downstream stress in higher-risk indicators.

Conversely, indicators associated with environmental sustainability, technological infrastructure, and gender equity—such as *mobile phones per 100 people*, *minimum species diversity*, *female landholdings*, and *functional integrity*—consistently register lower PF scores. This does not imply these indicators are unimportant, but rather that their position within the influence network makes them less likely to be overwhelmed by other variables. They may be more stable structurally but are also less exposed to systemic feedback loops. Interestingly, this places in contrast to high-PF indicators: while they may not trigger systemic collapse when disturbed, they may also be slower to reflect or absorb changes initiated elsewhere.

The presence of governance indicators such as *government effectiveness* and *open budget index* in the mid-to-low PF range is noteworthy and aligns with the theoretical emphasis in Schneider et al. (2025). Governance variables, despite their high leverage (as shown in PE scores), are not themselves structurally fragile; they exert influence rather than absorb it. Their stability

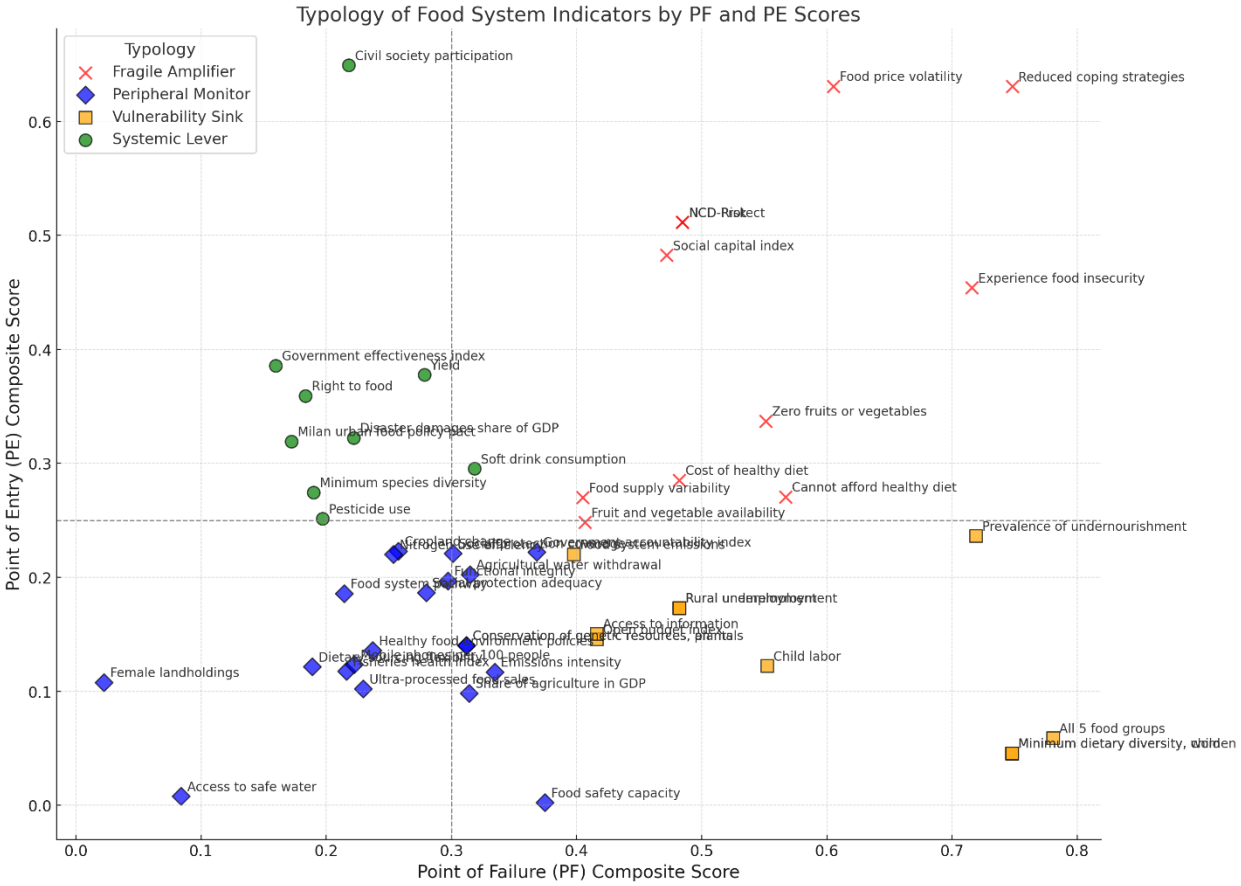
reinforces the broader theory that governance functions as an anchor for resilience—capable of directing systemic change without being destabilized by it.

Overall, this PF ranking provides a powerful complement to the PE index. While PE identifies the system's levers, PF exposes its vulnerabilities. Together, they map out the dual imperative of transformation: intervening in high-leverage nodes while stabilizing fragile outcomes. The findings reinforce the central conclusion of Schneider et al. (2025): food systems must be governed as interdependent networks, where success depends not only on triggering progress but on preventing collapse. Designing interventions without understanding fragility would be akin to engineering a machine for acceleration while ignoring its weakest links. The PF composite score helps ensure that vulnerability is no longer invisible in the architecture of transformation.

The typology (Figure 4) generated from the PF and PE composite scores offers a compelling visual and analytical tool for distinguishing the strategic roles of different food systems indicators. This layout reveals not only which components are most fragile or influential but also how they relate structurally and strategically to one another within the broader food systems network.

Indicators in the upper-left quadrant are classified as systemic levers. These components combine high systemic influence (reflected in high PE scores) with structural stability (low PF scores), making them ideal targets for proactive policy engagement. Their ability to transmit beneficial effects widely without amplifying fragility positions them as optimal sites for strategic interventions. These nodes often relate to governance capacity, participation, or enabling infrastructures—factors known to catalyze transformation across multiple dimensions of food systems (Schneider et al., 2025).

Figure 4: Network typology



Source: Author's

In contrast, fragile amplifiers, located in the upper-right quadrant, represent a dual-edged challenge. These indicators are both highly influential and acutely vulnerable. While they can rapidly spread beneficial impacts, they are equally capable of magnifying disruptions. Their centrality means any misalignment—such as poorly designed subsidies or market shocks—can reverberate widely, often with unintended consequences. Managing such nodes requires a combination of leverage and buffering strategies, aligning with the principle of "sensitive intervention points" in complex adaptive systems (Meadows, 1999).

The lower-right quadrant identifies vulnerability sinks—indicators that are structurally fragile but exert limited systemic influence. These are often outcome indicators, such as malnutrition rates or food insecurity levels, that bear the brunt of upstream failures. Their low PE scores suggest limited use as intervention hubs, yet their high PF profiles underline their role as stress absorbers. Stabilizing these components is essential not because they change the system, but because they reflect its failure.

Finally, peripheral monitors, in the lower-left quadrant, are both marginal in influence and relatively insulated from systemic shocks. While they may not serve as primary levers for transformation, they hold diagnostic value. Their movement can reveal underlying tensions or inequities in subdomains of the system—such as gender disparities in land ownership or regional infrastructure access—making them vital for inclusive, just policymaking.

Policy Implications

The application of network-based modeling to food systems, as presented by Schneider et al. (2025), marks a pivotal shift in how policymakers must approach food systems reform. Rather than viewing policies through sectoral or isolated lenses, the networked structure of global food systems compels a move toward intervention strategies that are both targeted and systemic. The identification of PEs and PFs through composite indexes—grounded in metrics such as centrality, clustering, and influence dispersion—provides not only diagnostic value but also prescriptive guidance.

At the core of the policy implications is the recognition that food systems function as complex adaptive systems, characterized by feedback loops, nonlinear responses, and tightly coupled interdependencies. This means that small, well-placed interventions can generate broad systemic effects—a concept long established in systems theory (Meadows, 1999)—and conversely, that policy misalignment at fragile nodes can trigger widespread dysfunction. Schneider et al. (2025) argue that governance and resilience are foundational for transformative change precisely because they offer both leverage and stability. Governance-related indicators such as *civil society participation*, *government effectiveness*, and *right to food* emerged in their analysis as the most connected and influential nodes—structural hubs through which influence flows across nutrition, environmental management, equity, and market access.

The PE analysis confirms this claim with empirical clarity. These governance nodes score highest on composite PE indexes, suggesting that institutional reform, transparency, and participatory governance are not simply enabling factors but primary levers for reorienting food systems. From a policy standpoint, this means investments in strengthening state capacity, participatory mechanisms, and rule-of-law institutions are not secondary to agricultural productivity or dietary programs—they are foundational.

Equally important, the PF analysis surfaces fragile endpoints that require policy stabilization. Indicators like *prevalence of undernourishment*, *cost of healthy diet*, and *experience of food insecurity* show high in-degree centrality and clustering, marking them as convergence points of systemic risk. These are not isolated outcomes but volatile junctions where pressures from pricing, access, climate, and governance accumulate. Schneider et al. (2025) stress that failure

to stabilize these nodes can lead to divergence from sustainability trajectories, overwhelming systems and undermining well-intentioned reforms.

The policy implication here is twofold. First, such nodes must be buffered with protective policies: cash transfers, food subsidies, nutritional safety nets, and social protection measures that insulate vulnerable populations from systemic volatility. Second, these must be aligned across policy domains to prevent contradictory signals—one of the key causes of system destabilization identified in the Schneider et al. model. For example, a subsidy that promotes fertilizer use without coordinated regulation of nutrient runoff may produce conflicting outcomes in productivity versus environmental sustainability.

Another critical implication relates to timing and adaptability. The system dynamics model outlined in our model includes response delays (τ_i) and behavioral context parameters (C_i), acknowledging that policy impacts are rarely immediate. Hence, policies must be adaptive, evolving in intensity and direction in response to lagged behavioral shifts. This supports a real-time policy monitoring and feedback approach, where interventions are recalibrated based on system signals rather than locked into static design.

In this context, the network analysis of PFs and PEs can serve as an operational tool for policy prioritization, sequencing, and synchronization. High-PE nodes can guide where to initiate policy action, while high-PF nodes signal where to focus stabilization efforts. Importantly, some nodes will simultaneously be high in both categories—fragile and influential. These dual-role nodes present strategic windows for transformation but also require careful risk management to avoid policy backfire.

Ultimately, the policy takeaway is that resilient transformation requires both systemic insight and structural leverage. Policies must be judged not only by their direct effects but by their position within the network: how influence propagates, where it converges, and whether it contributes to self-reinforcing stability or destabilizing feedback. By formalizing these concepts into a model that is both empirically grounded and practically oriented, the study equips policymakers with a roadmap for navigating complexity with precision.

Conclusion

This paper confirms that sustainable and equitable food futures will not be achieved through isolated interventions, but through a profound understanding of the structural architecture of influence, vulnerability, and feedback embedded within food systems. By applying network theory and dynamic systems modeling, this work introduces a framework to diagnose points of failure (PFs)—nodes where systemic risk accumulates—and points of entry (PEs)—nodes where targeted interventions can propagate widespread change.

The findings presented here resonate strongly with those of Schneider et al. (2025), who identified governance and resilience as critical levers for transformation. Their analysis, rooted in expert-elicited causal mappings of 50 global food systems indicators, laid the groundwork for recognizing that the position of an indicator within a system's structure—its centrality, influence, or exposure—can profoundly determine both the outcomes it reflects and the role it can play in systemic change. This study extends that insight with a data-driven complement: by calculating composite PF and PE indexes based solely on adjacency matrix-derived metrics, we provide a replicable, scalable tool for identifying leverage points and risk nodes across various contexts.

The implications are clear. Indicators such as civil society participation, government effectiveness, and the right to food repeatedly emerge as high-PE components—capable of shaping the trajectories of multiple subsystems, from nutritional adequacy to environmental resilience. Simultaneously, nodes like prevalence of undernourishment, cost of a healthy diet, and experience of food insecurity surface as high-PF components, vulnerable to upstream shocks and requiring structural insulation. These findings underscore that governance is not a peripheral factor but a systemic actuator, while nutritional and equity outcomes are not terminal points but fragile endpoints whose destabilization can reverse progress across multiple SDGs.

Furthermore, the presence of feedback loops, behavior-mediated delays, and policy resistance in the dynamic modeling reinforces the need for adaptive policy design—interventions that not only consider direct impacts but anticipate second-order effects and evolving system responses. This echoes the broader conclusion from Schneider et al. (2025) and other systems evidence (Meadows, 1999; Ostrom, 2009) that policy success in complex systems depends as much on timing and alignment as on magnitude.

Looking forward, future research must explore the integration of non-adjacency matrix metrics to capture system dynamics beyond structural topology. While adjacency-based indexes such as degree and centrality offer a foundational view of influence and vulnerability, they do not account for critical features such as temporal lags, policy responsiveness, actor heterogeneity, or contextual behavioral parameters. Incorporating dynamic features—such as system stability via Jacobian analysis, empirical policy elasticity (β_i), response delays (τ_i), and real-world feedback delays—would enable more realistic modeling of intervention outcomes. Moreover, embedding empirical data on institutional trust, political feasibility, and behavioral uptake into systems modeling could enhance the predictive accuracy of entry point effectiveness. These future directions would enrich the utility of PF/PE frameworks not only as diagnostics but as operational tools for anticipatory governance.

While our typology identifies indicators with high potential for systemic influence or fragility, their application must be contextualized. National institutions, political economy dynamics, and cultural factors significantly shape the effectiveness of any policy intervention. As such, we urge policymakers to pair these findings with local diagnostics and participatory processes. The typology should be seen as a guide for strategic targeting—not a prescriptive blueprint.

References

Åström, Karl J., and Richard M. Murray. *Feedback Systems: An Introduction for Scientists and Engineers*. Princeton: Princeton University Press, 2008.

Herforth, A., A.L. Bellows, Q. Marshall, R. McLaren, T. Beal, S. Nordhagen, R. Remans, N. Estrada Carmona, and J. Fanzo. (2022). "Diagnosing the performance of food systems to increase accountability toward healthy diets and environmental sustainability." *PLoS One* 17 (7): e0270712. https://doi.org/10.1371/journal.pone.0270712

Godfray, H. Charles J., John R. Beddington, Ian R. Crute, Lawrence Haddad, David Lawrence, James F. Muir, Jules Pretty, Sherman Robinson, Sandy M. Thomas, and Camilla Toulmin. "Food security: The challenge of feeding 9 billion people." *Science* 327, no. 5967 (2010): 812–818.

Headey, D., & Fan, S. (2008). Anatomy of a crisis: the causes and consequences of surging food prices. *Agricultural Economics*, 39(s1), 375–391. https://doi.org/10.1111/j.1574-0862.2008.00345.x

Laborde, D., Martin, W., Swinnen, J., & Vos, R. (2020). COVID-19 risks to global food security. *Science*, 369(6503), 500–502. https://doi.org/10.1126/science.abc4765

May, Robert M. "Will a large complex system be stable?" *Nature* 238, no. 5364 (1972): 413–414.

Meadows, D. H. (1999). *Leverage points: Places to intervene in a system*. Sustainability Institute. https://donellameadows.org/archives/leverage-points-places-to-intervene-in-a-system/

Meadows, Donella H. *Thinking in Systems: A Primer*. White River Junction, VT: Chelsea Green Publishing, 2008.

Odum, E. P. (1983). Basic Ecology. Saunders College Publishing.

Ostrom, E. (2009). A general framework for analyzing sustainability of social-ecological systems. *Science*, 325(5939), 419–422. https://doi.org/10.1126/science.1172133

Ostrom, E. (2009). A general framework for analyzing sustainability of social-ecological systems. *Science*, 325(5939), 419–422. https://doi.org/10.1126/science.1172133

Schneider, K. R., Fanzo, J., Springmann, M., Remans, R., Davis, K., Nisbett, N., ... & Barrett, C. B. (2025). *Governance and resilience as entry points for transforming food systems in the countdown to 2030*. Nature Food, 6, 105–116. https://doi.org/10.1038/s43016-024-01109-4
Scheffer, Marten, Steve R. Carpenter, Tim M. Lenton, Jordi Bascompte, William Brock, Victor Dakos, Johan van de Koppel et al. "Anticipating critical transitions." *Science* 338, no. 6105 (2012): 344–348.

Vervoort, J. M., Fanzo, J., et al. (2023). *Food Systems Countdown Initiative 2023: Data and Methodological Protocols*. FSCI Technical Paper.

Willett, W., Rockström, J., Loken, B., Springmann, M., Lang, T., Vermeulen, S., … Murray, C. J. L. (2019). Food in the Anthropocene: The EAT–Lancet Commission on healthy diets from sustainable food systems. *The Lancet, 393*(10170), 447–492. https://doi.org/10.1016/S0140-6736(18)31788-4

Annex A: Mathematical formulas for each adjacency matrix-based structural metric used to compute Points of Failure (PF) and Points of Entry (PE) indices

PF (Point of Failure) Metrics

1. In-Degree centrality

$$\text{InDeg}_i = \sum_{j=1}^{N} A_{ij}$$

Measures how many edges point **into** node i; i.e., how much a node is influenced by others.

2. Eigenvector centrality

$$\text{EC}_i = \frac{1}{\lambda} \sum_{j=1}^{N} A_{ij} \cdot \text{EC}_j$$

- Solves the eigenvector equation $Av = \lambda vA$
- A node is important if it's connected to other important nodes.

3. Clustering Coefficient (Undirected approximation)

$$C_i = \frac{2T_i}{k_i(k_i - 1)}$$

- T_i: number of triangles through node i
- k_i: number of neighbors of i
- Measures the density of the local neighborhood — potential for local feedback loops.

PE (Point of Entry) metrics

4. Out-degree centrality

$$\text{OutDeg}_i = \sum_{i=1}^{N} A_{ji}$$

- Measures how many edges point out of node j; i.e., how much a node influences others.

5. PageRank

$$PR = \frac{1 - d}{N} + d \sum_{j \in \text{In}(i)} \frac{PR_j}{\text{OutDeg}_\text{i}}$$

- d: damping factor (typically 0.85)
- Captures long-term importance by iteratively redistributing weights over the graph.

6. Betweenness centrality

$$BC = \sum_{s \neq i \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}}$$

- σ_{st}: number of shortest paths from node s to node t
- $\sigma_{st}(i)$: number of those paths that pass through i
- Identifies nodes that control information flow.

7. Average path length (Inverse)

$$APL_I^{-1} = \frac{1}{\frac{1}{|R_i|}\sum_{j \in R_i, j \neq i} d(i,j)}$$

- R_i: nodes reachable from i
- $d(i,j)$: shortest path from i to j
- Inverse average distance → higher score means closer to more nodes (more leverage).

Composite index formulas (Equal weights)

PF composite Index:

$$\text{PF}_i = \frac{1}{3}(\text{InDeg}_i^{\text{norm}} + \text{EigenCentrality}_i^{\text{norm}} + \text{Clustering}_i^{\text{norm}})$$

PE composite Index:

$$\text{PE}_i = (\text{OutDeg}_i^{\text{norm}} + \text{PageRank}_i^{\text{norm}} + \text{Betweenness}_i^{\text{norm}} + \text{InvAvgPathLength}_i^{\text{norm}})$$

Each term is normalized to [0,1] before averaging.

ALL IFPRI DISCUSSION PAPERS

All discussion papers are available **here**

They can be downloaded free of charge

INTERNATIONAL FOOD POLICY RESEARCH INSTITUTE
www.ifpri.org

IFPRI HEADQUARTERS
1201 Eye Street, NW
Washington, DC 20005 USA
Tel.: +1-202-862-5600
Fax: +1-202-862-5606
Email: ifpri@cgiar.org