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Hidden Vulnerability Under Global Shocks: A Dynamic Resilience Index for Import-Dependent Food Systems—Evidence from Jordan

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ABSTRACT: This study examines the evolution of cereal import dependence and food system resilience in Jordan over the period 1961–2023 using FAO data. Import dependence is measured by the Import Dependence Ratio (IDR), while a Dynamic Resilience Index (DRI) is developed to integrate dependence levels with temporal volatility. The results reveal a structural shift from a moderately dependent and volatile system to one characterized by persistently high and seemingly stable import dependence since the late 1970s. However, this apparent stability masks latent vulnerability, as the DRI indicates declining resilience driven by the interaction between high dependence and volatility. The analysis further shows that major global shocks (2008, 2020, and 2022) exert a significant negative effect on resilience. Scenario analysis suggests convergence toward a structurally low-resilience equilibrium under current conditions. The findings highlight the need for policies targeting both dependence reduction and volatility management.

KEYWORDS: Dynamic resilience index, Food system resilience, Global shocks, Import dependence, Volatility

1. INTRODUCTION

Food security continues to pose a major structural challenge for economies with limited natural resources. In many of these countries, domestic agricultural production is constrained not only by policy limitations but also by persistent physical constraints, including water scarcity, limited arable land, and growing demographic pressure. Under such conditions, dependence on international food markets is not simply a policy preference but an inherent feature of the food system. Jordan provides a clear example of this reality. Its cereal supply relies heavily on imports, leaving the national food system continuously exposed to fluctuations in global food prices, supply-chain disruptions, and external shocks (FAO, 2021; World Bank, 2022).

While trade integration has improved food availability, it has also increased exposure to new sources of vulnerability, particularly during periods of global instability. The food price crisis of 2008, the COVID-19 pandemic, and the geopolitical disruptions of 2022 demonstrated how rapidly external shocks can spread through domestic food systems and intensify existing weaknesses (Headey & Fan, 2008; Timmer, 2010). These events also highlighted an important limitation of conventional assessment tools. Indicators such as the Import Dependency Ratio (IDR) provide a useful measure of reliance on external markets at a given point in time, yet they offer little insight into how that dependence changes—or becomes more fragile—under adverse conditions. Consequently, an apparently stable level of import dependence may conceal underlying vulnerabilities that emerge only when food systems are subjected to external stress.

These limitations have encouraged increasing attention to the concept of food system resilience, which emphasizes the ability of food systems to absorb shocks, adapt to changing conditions, and maintain stable food supplies over time (Tendall et al., 2015; Béné et al., 2016). Despite its growing importance in the literature, the concept remains insufficiently operationalized in empirical research. Existing approaches rarely provide an integrated quantitative framework capable of capturing both the level of import dependence and the way that dependence varies over time. As a result, an important gap remains between the theoretical understanding of resilience and its practical measurement in import-dependent food systems.

To address this gap, the present study develops a Dynamic Resilience Index (DRI) that combines cereal import dependence with its temporal volatility within a single analytical framework. Instead of treating import dependence as a static outcome, the proposed index conceptualizes it as a dynamic process shaped jointly by external exposure and structural stability. Using annual data for Jordan covering the period 1961–2023, the study applies the Autoregressive Distributed Lag (ARDL) approach to distinguish short-run adjustments from long-run structural dynamics. Major global shock episodes are explicitly incorporated into the empirical analysis to evaluate how resilience behaves under conditions of external stress.

The study contributes both methodologically and empirically to the literature on food system resilience. Methodologically, it introduces a Dynamic Resilience Index that extends conventional measures of import dependence by incorporating temporal instability into the assessment of vulnerability. Empirically, it demonstrates how this framework can provide a more comprehensive understanding of vulnerability in import-dependent food systems and offers a practical basis for resilience assessment, future research, and policy-oriented risk monitoring.

2. LITERATURE REVIEW

2.1 Theoretical Framework

Conventional indicators of food security, particularly those based on import dependence, provide valuable information about a country's exposure to external food markets. However, they offer only a static representation of that exposure and cannot explain why food systems with comparable levels of import dependence often respond differently to external shocks. This limitation reflects an important conceptual issue: understanding food system resilience requires considering not only the degree of dependence but also how stable that dependence remains over time. The interaction between these two dimensions ultimately shapes the vulnerability of import-dependent food systems under changing conditions.

Import dependence should not be regarded as a weakness in itself. In countries facing severe resource constraints, reliance on international markets often represents the most economically rational means of securing food supplies (Timmer, 2010). Vulnerability arises when a high degree of dependence is accompanied by instability, leaving food systems increasingly exposed to external shocks despite appearing stable under normal conditions. From this perspective, resilience depends on both the extent of external exposure and the stability of that dependence over time. To operationalize this concept, the present study develops a Dynamic Resilience Index (DRI) that integrates the level of cereal import dependence with its temporal variability in a single quantitative measure.

2.1.1 Food Security and Import Dependence

Food security is conventionally defined across three intersecting dimensions—availability, access, and stability (FAO, 2021). For import-dependent economies, the stability dimension is most consequential: it is where the domestic food system interfaces most directly with global market volatility. In countries such as Jordan, where water scarcity and limited arable land structurally constrain domestic production, reliance on cereal imports is not a policy failure but a binding structural condition. High import dependence in such contexts is economically rational (Timmer, 2010), yet it simultaneously concentrates risk—leaving the food system exposed to price shocks, supply disruptions, and geopolitical instability in ways that domestically oriented systems are not.

2.1.2 Dependence, Vulnerability, and the Limits of Market Integration

Trade integration enhances supply flexibility and allocative efficiency, but does not on its own reduce vulnerability. When dependence is deep and risk management mechanisms are weak, external shocks transmit directly into domestic food systems rather than being buffered (Headey & Fan, 2008). Import dependence is therefore best understood as a dual-edged phenomenon whose implications depend less on its magnitude than on the system's capacity to manage accompanying instability. Reliance on a concentrated set of suppliers or trade corridors amplifies this exposure further, underscoring the importance of supply diversification (Chaturvedi, 2024; Das & Bhandari, 2025).

2.1.3 Food System Resilience: From Crisis Response to Dynamic Capacity

Food system resilience refers to the capacity to absorb shocks, adapt to disturbances, and sustain core functions over time (Tendall et al., 2015). What distinguishes this framework from earlier crisis-response models is its emphasis on continuity under persistent uncertainty rather than recovery from discrete events (Béné et al., 2016). Resilience is not a threshold condition but a dynamic property that varies with the nature of the stressor and the structural characteristics of the system—a framing made particularly relevant by the recurring, overlapping shocks of the 2008 price crisis, the COVID-19 pandemic, and the 2022 geopolitical disruptions.

2.1.4 The Static Bias of Conventional Indicators and the Dynamic Dimension of Vulnerability

The IDR captures a system's position at a given point in time without revealing how that position shifts under pressure. A country may exhibit a stable IDR while underlying supply chains become progressively more fragile—a limitation reflecting a broader conceptual issue: vulnerability is shaped not only by the level of exposure but by its variability over time, with instability increasing susceptibility to shocks (FAO, 2018).

Agricultural commodity markets are a major source of this instability. Global cereal price volatility is influenced by geopolitical disruptions, climate events, trade policy shifts, and macroeconomic conditions such as inflation and exchange rate movements (Gilbert & Morgan, 2010; Horák, 2026). These fluctuations exhibit cross-market transmission effects (Nazlioglu & Soytas, 2011; Ghoddusi, 2016) and may persist over time (Patare et al., 2024). For highly import-dependent economies, the central issue is therefore not the existence of volatility itself, but the capacity of the domestic food system to absorb it without translating it into food insecurity.

2.1.5 Linking Theory to the DRI Framework

Fragility in import-dependent food systems arises from the interaction between dependence and instability, not from either dimension in isolation. A highly dependent system with stable, diversified supply chains may be more resilient than a moderately dependent one subject to recurring disruptions—a distinction that conventional static indicators cannot capture. The DRI addresses this by integrating the level of import dependence with its volatility over time, producing a composite measure that is both analytically grounded and policy-relevant. The following section develops this framework and positions it within the broader empirical literature.

2.2 Previous Studies

Import dependence is a common feature of resource-constrained economies; however, its implications depend on a country's capacity to manage associated risks. While it may not be inherently problematic (Clapp, 2017), trade interdependence can amplify the transmission of shocks across countries (Puma et al., 2015).

Global crises further reveal underlying structural vulnerabilities in food systems, as evidenced during major food crises and the COVID-19 pandemic, which disrupted global supply chains and heightened sensitivity to external shocks (Headey & Fan, 2008; Laborde et al., 2020).

Price volatility in agricultural markets is closely linked to macroeconomic factors such as inflation and exchange rates (Headey & Fan, 2008), and reflects broader mechanisms of shock transmission across interconnected markets (Nazlioglu & Soytas, 2011; Ghoddusi, 2016).

From a measurement perspective, most studies rely on the IDR as a primary indicator of exposure; however, this measure remains static and therefore limited in capturing temporal variability in vulnerability (Anderson & Nelgen, 2012). Recent research has increasingly focused on developing composite resilience indicators. For example, KC et al. (2025) proposed the Food Systems Resilience Score (FSRS), a multidimensional framework for assessing resilience across national food systems. Similarly, the Food Systems Dashboard framework provides a broader indicator-based approach for monitoring food system conditions and resilience dimensions (Fanzo et al., 2020). While these frameworks offer comprehensive multidimensional assessments, the present study focuses specifically on the interaction between import dependence and temporal instability, providing a targeted measure of dynamic vulnerability through the Dynamic Resilience Index (DRI).

In applied contexts, Jordan represents a typical case of a resource-constrained, import-dependent economy, with cereal import dependence frequently exceeding 90% according to FAO and World Bank data. This structural reliance, driven by water scarcity and climate constraints, increases the sensitivity of the food system to external shocks.

2.3 Research Gap

Current research on food security has made substantial progress in examining the implications of import dependence. Nevertheless, most empirical studies continue to assess dependence using static indicators that capture its level while overlooking its temporal variability and evolving instability. Consequently, these approaches provide only a partial understanding of food system vulnerability, particularly during periods of recurring shocks and heightened volatility.

An additional limitation is that existing studies have not developed an integrated quantitative framework capable of simultaneously capturing both the degree of import dependence and its fluctuations over time. As a result, the dynamic nature of vulnerability remains insufficiently represented in empirical assessments.

The present study addresses this limitation by developing the Dynamic Resilience Index (DRI), which combines the level of import dependence with its temporal variability within a single analytical framework. By integrating these two dimensions, the DRI moves beyond static measurement toward a dynamic assessment of food system vulnerability and its response to external shocks.

2.4 Conceptual Model for Dynamic Food System Resilience

Figure 1 presents the conceptual framework of the study, where food system resilience is modeled as a dynamic outcome resulting from the interaction between import dependence, its volatility, and exposure to global shocks.

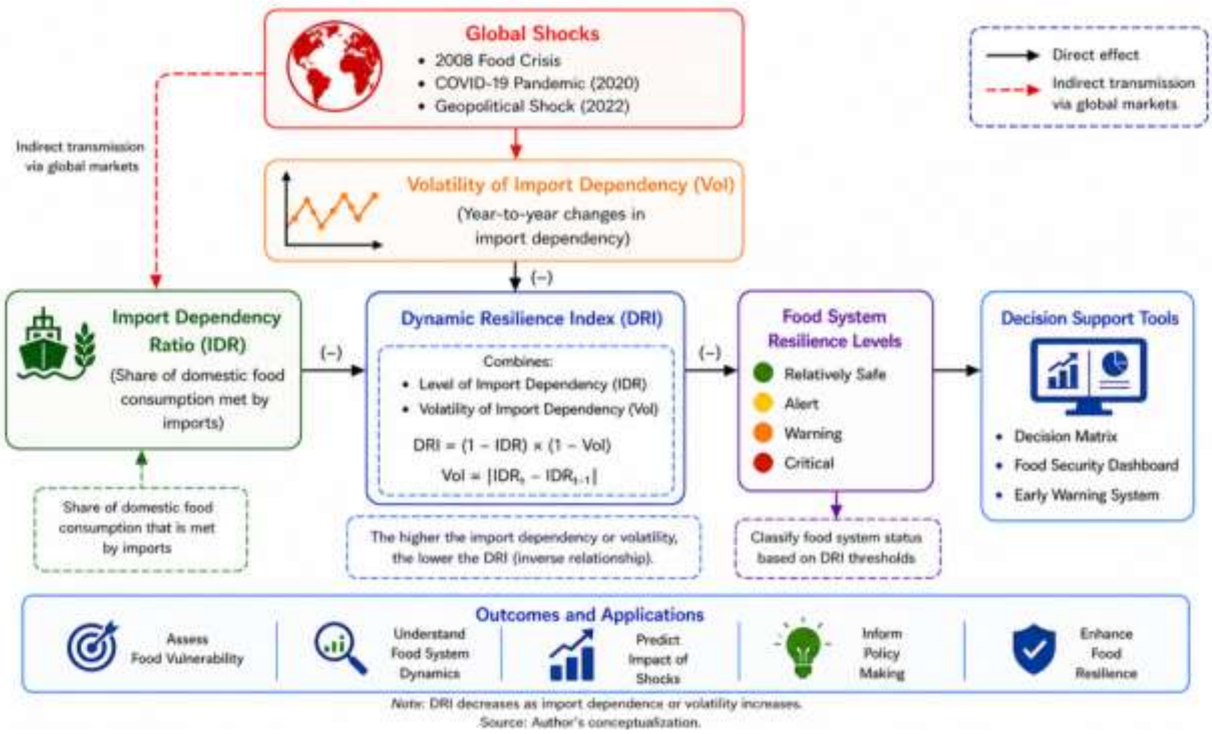

Figure 1. Conceptual Model for dynamic food system resilience

The model centers on the DRI, which integrates the level of IDR and its temporal volatility (VOL2). Higher dependence and instability jointly reduce resilience by increasing exposure to external shocks.

IDR represents structural reliance on imported food supplies, while volatility captures instability in dependence over time. Major global disruptions—including the 2008 food crisis, the COVID-19 pandemic, and the 2022 geopolitical shock—are incorporated as exogenous drivers affecting food systems through supply and price transmission channels.

The interaction of these components determines overall resilience, with DRI outcomes translated into operational categories (Safe, Alert, Warning, and Critical) to support policy interpretation. The framework further links resilience assessment to decision-support applications, including early warning systems and policy monitoring tools.

2.5 Hypotheses Development

Based on the theoretical framework linking import dependence, volatility, and food system resilience, the study formulates the following testable hypotheses.

H1: Higher levels of import dependence are associated with lower resilience outcomes as measured by the Dynamic Resilience Index (DRI).

H2: Greater instability in import dependence is associated with lower resilience outcomes as measured by the Dynamic Resilience Index (DRI).

H3: Major global shocks are associated with lower resilience outcomes within import-dependent food systems.

3. DATA AND METHODOLOGY

3.1 Data

This study relies on Food Balance Sheets data obtained from the Food and Agriculture Organization of the United Nations (FAO). The dataset provides consistent long-term series on production, imports, exports, and domestic supply, allowing for the construction of key food security indicators over the study period.

3.2 Research Design

The study adopts a quantitative descriptive–analytical time-series approach to examine the evolution of cereal import dependence and food system resilience in Jordan over the period 1961–2023. The analysis focuses on identifying long-term trends, short-term fluctuations, and structural patterns, as well as constructing a composite indicator—the (DRI)—to capture the dynamic behavior of food system vulnerability.

3.3 Variables and Data Construction

The analysis is based on the following core variables: Domestic production, imports, exports and domestic supply quantity.

3.4 Indicator Construction and Interpretation

3.4.1 Import Dependency Ratio (IDR)

The IDR is calculated as the ratio of imports to domestic supply, with domestic supply obtained from FAOSTAT or estimated as:

$$\textit{Domestic Supply}_t = \textit{Production}_t + \textit{Imports}_t - \textit{Exports}_t \qquad (1)$$

This ratio measures exposure to external markets, where values close to zero indicate low dependence, values near one indicate high dependence, and values above one may reflect data adjustments or stock variations.

3.4.2 Resilience Gap

The Resilience Gap represents the difference between domestic self-sufficiency and import dependence, capturing the margin available for food system resilience.

It is defined as:

$$\textit{Resilience Gap}_t = 1 - \textit{IDR}_t \qquad (2)$$

3.4.3 Volatility Measure (VOL2)

To capture temporal instability in import dependence, VOL2 is calculated as the squared deviation of the IDR from its mean over the study period:

$$\textit{VOL2}_t = (\textit{IDR}_t - \textit{mean}\ (\textit{IDR}))^2 \qquad (3)$$

where mean(IDR) represents the average import dependency ratio over the study period. This measure captures the magnitude of fluctuations and is used as the volatility component in the DRI.

The squared-deviation formulation was selected because it captures the magnitude of departures from the long-run dependence pattern while assigning proportionally greater weight to larger fluctuations. This property is particularly relevant in food security analysis, where extreme instability episodes may generate disproportionately larger resilience consequences than small year-to-year variations. In addition, the measure is transparent, easily replicable, and suitable for long historical datasets where more parameter-intensive volatility models may be less practical.

3.4.5 Dynamic Resilience Index (DRI)

The DRI is constructed as a composite measure integrating import dependence and volatility. This index captures both structural exposure and instability over time.

$$\textit{DRI}_t = (1 - \textit{IDR}_t) \times (1 - \textit{VOL2}_t) \qquad (4)$$

$$\textit{DRI}_t = \textit{Resilience Gap}_t \times (1 - \textit{VOL2}_t) \qquad (5)$$

Higher values indicate stronger resilience, while lower or negative values indicate greater vulnerability.

3.5 Theoretical Grounding and Originality of the Index

The IDR is a well-established indicator in the food security literature, widely used to assess reliance on external food supplies, while volatility is a recognized dimension of food system stability. What has received less analytical attention is their interaction—the compounding effect of high dependence and high instability on system-level vulnerability. The DRI addresses this gap by integrating both dimensions within a unified multiplicative framework, producing a dynamic measure of vulnerability that neither indicator captures independently.

Although the DRI builds on established concepts, its methodological contribution lies in operationalizing the interaction between dependence and instability through a direct multiplicative formulation. Rather than viewing import dependence as a static condition, the index conceptualizes vulnerability as a dynamic property shaped by the joint behavior of external exposure and temporal variability.

The multiplicative specification was chosen because vulnerability in import-dependent food systems arises from the interaction between dependence and instability rather than from either dimension alone. Unlike an additive formulation, which allows strength in one dimension to offset weakness in the other, the multiplicative structure captures the compounding nature of food system risk by penalizing situations in which both dependence and instability are elevated. Accordingly, the DRI operationalizes this interaction, providing a dynamic representation of resilience that extends beyond conventional composite measures.

3.6 Scope and Applicability of the DRI

The DRI is most analytically suited to import-dependent, resource-constrained economies where external market exposure is a structural feature of the food system rather than a policy variable (FAO, 2021; Clapp, 2017). In such contexts, the interaction between dependence and volatility is not incidental but constitutive of food security risk, and its measurement has direct implications for monitoring and policy design. The index's explanatory power increases under conditions of elevated global market volatility—particularly during food price crises and geopolitical disruptions—where instability functions as the primary transmission channel through which external shocks reach domestic food systems (Headey & Fan, 2008; Gilbert & Morgan, 2010).

Its applicability is more limited in food systems characterized by stable domestic production or persistently low variability in import dependence, where the interaction term carries less discriminatory power.

The volatility component is operationalized using squared deviations from the long-run mean of import dependence (VOL2). This specification provides a transparent measure of instability by assigning greater weight to larger departures from the historical dependence pattern. Nevertheless, alternative volatility measures such as rolling standard deviations, GARCH-based specifications, or regime-switching approaches may capture additional dimensions of temporal instability and could be explored in future research.

Within these boundaries, the DRI offers a practically implementable and analytically coherent tool for assessing food system resilience in volatile environments. Its value lies not in replacing existing indicators but in extending the analytical frame to capture a dimension of vulnerability that static measures systematically overlook.

3.7 Econometric Model Specification

In addition to the descriptive analysis, this study employs an econometric framework to examine the dynamic relationships between food system resilience and its key determinants, namely import dependence, its volatility, and exposure to external shocks.

The conceptual (theoretical) model is specified as follows:

$$DRI_t = \beta_0 + \beta_1 \, IDR_t + \beta_2 \, VOL2_t + \beta_3 \, Shock_t + \varepsilon_t \qquad (6)$$

where:

DRIt denotes the Dynamic Resilience Index

IDRt represents the level of import dependence

VOL2t captures the volatility of import dependence

SHOCKt is a dummy variable representing major global shocks (2008, 2020, and 2022)

εt is the error term

Because the Dynamic Resilience Index (DRI) is constructed using both import dependence (IDR) and its volatility component (VOL2), the econometric model is not intended to establish independent causal effects in the strict econometric sense. Instead, the ARDL framework is employed as a dynamic consistency and decomposition approach that examines how the interaction between dependence, instability, and external shocks is reflected in resilience outcomes over time.

Accordingly, the estimated coefficients should be interpreted as indicators of the relative contribution and dynamic association of these components within the resilience framework rather than as evidence of fully independent causal relationships.

3.8 Methodological Clarification on DRI Construction and Econometric Interpretation

The Dynamic Resilience Index (DRI) is intentionally constructed as a composite indicator combining two conceptually distinct dimensions of food system vulnerability: structural exposure to external food supplies, represented by the Import Dependency Ratio (IDR), and instability in that exposure, represented by the volatility measure (VOL2).

Because DRI is mathematically derived from these components, a potential mechanical relationship exists between the index and its constituent variables. Consequently, the econometric analysis should not be interpreted as a strict causal identification exercise in which IDR and VOL2 are treated as fully independent determinants of an unrelated outcome variable.

Instead, the ARDL framework is employed as a dynamic decomposition and consistency assessment approach. Its purpose is to evaluate how the resilience index behaves over time in response to changes in its underlying structural dimensions and to examine whether the proposed framework generates coherent long-run and short-run resilience patterns under conditions of external shocks and market instability.

Accordingly, the estimated coefficients are interpreted as indicators of the relative contribution and dynamic association of dependence and instability within the resilience framework rather than as evidence of fully independent causal effects.

This approach is consistent with a broader literature on composite indices, where econometric analysis is often used to assess the dynamic behavior, stability, and policy relevance of index components rather than to establish strict causal relationships among mathematically independent variables.

3.9 ARDL Estimation Framework

The original volatility measure (VOL) was found to be integrated of order I(2). Therefore, the transformed volatility specification (VOL2), which satisfies the integration requirements of the ARDL framework, was employed in the empirical estimation.

Consistent with the resilience framework described above, the empirical specification used for estimation is:

$$\mathbf{DRI_t = \beta_0 + \beta_1 IDR_t + \beta_2 VOL2_t + \beta_3 Shock_t + \varepsilon_t \ (7)}$$

Within this specification, the estimated coefficients are interpreted as indicators of the relative contribution and dynamic association of the underlying resilience dimensions rather than as evidence of fully independent causal effects.

3.10 Estimation Strategy

The study employs the ARDL approach to examine short- and long-run relationships among DRI, IDR, and VOL2, given its suitability for variables integrated of order I(0) and I(1), provided none is I(2).

3.11 Shock Variable

A shock dummy captures major global disruptions (2008, 2020, 2022) and is treated as strictly exogenous, allowing identification of the independent impact of external shocks on resilience.

The selected shock years represent major externally generated disruptions that affected global food markets through distinct transmission mechanisms. The 2008 food crisis reflected a period of exceptional international food price escalation, the 2020 shock captured the global supply-chain disruptions associated with the COVID-19 pandemic, and the 2022 shock reflected geopolitical disturbances affecting global grain markets. These events were selected because of their documented international relevance and their potential influence on import-dependent food systems.

3.12 Error Correction Representation

Short-run dynamics are modeled using the ECM:

$$\Delta DRI_t = \alpha_0 + \sum \alpha_i \Delta X_t - i + \lambda ECM_{t-1} + u_t \qquad (8)$$

where:

ECMt-1 represents the lagged error correction term

λ captures the speed of adjustment toward equilibrium

A negative and statistically significant λ confirms the existence of a stable long-run relationship.

The model tests the effects of import dependence (β_1), volatility (β_2), and shocks (β_3) on resilience. Negative and significant coefficients indicate that higher dependence, instability, and external shocks reduce food system resilience.

3.13 Analysis Procedures

The empirical analysis followed a structured workflow. After data preparation and descriptive analysis, resilience conditions were classified using the proposed Dynamic Resilience Index (DRI). Time-series properties were assessed before estimating the ARDL model and testing for long-run and short-run relationships. Diagnostic and stability tests were then performed to verify model adequacy, and the results were interpreted in the context of Jordan's food system resilience and policy implications.

3.14 Conceptual and Operational Definitions

This study employs key concepts related to food security and resilience, defined both conceptually and operationally to ensure consistency with the analytical framework.

1.Food Security

Food security is defined as a condition in which all people have physical and economic access to sufficient, safe, and nutritious food (FAO, 2006). In this study, it is operationalized through availability and stability, proxied by import dependence and its variability, using the IDR and the DRI.

2.Food System Resilience

Food system resilience refers to the capacity to absorb shocks, adapt to disruptions, and maintain food supply (Tendall et al., 2015; Béné et al., 2016). It is measured using the Dynamic Resilience Index (DRI), which integrates import dependence and its volatility.

3.Import Dependency Ratio (IDR)

The IDR represents the share of imports in total domestic food supply (FAO). It is calculated as the ratio of imports to domestic supply (see Equation 2).

4.Resilience Gap

The Resilience Gap reflects the margin of resilience and is defined as the complement of IDR (see Equation 3).

5. Volatility (VOL2)

Volatility refers to temporal instability in import dependence (Anderson & Nelgen, 2012). In this study, it is operationalized through VOL2 and incorporated into the DRI to capture the stability dimension of the food system.

6. Dynamic Resilience Index (DRI)

The DRI is a composite indicator used to assess food system resilience dynamically by combining exposure and stability dimensions. Higher values indicate stronger resilience, while lower or negative values signal greater vulnerability.

7.Decision Matrix

The decision matrix translates DRI values into operational categories (Relatively Safe, Alert, Warning, Critical) based on empirically derived thresholds, supporting policy decision-making.

4. RESULTS AND DISCUSSION

4.1 Descriptive and Structural Analysis

Table 1 presents descriptive statistics for the Import Dependency Ratio (IDR) and the Resilience Gap over the study period (1961–2023).

Table 1. Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max	N
IDR	0.858	0.214	0.249	1.082	63
Resilience Gap	0.142	0.214	−0.082	0.751	63

The high average IDR (0.858) reflects persistent structural reliance on cereal imports, with a maximum exceeding unity (1.082) during episodes of extreme dependence. The Resilience Gap averages just 0.142, with negative minimum values (−0.082) marking periods of realized vulnerability. The shared standard deviation (0.214) across both variables indicates substantial temporal variability—a pattern that motivates the DRI as a dynamic complement to static indicators.

4.1.1 Long-Term Trends in Import Dependence and Resilience

Figure 2 traces the evolution of the IDR and Resilience Gap in Jordan from 1961 to 2023, revealing a persistent inverse relationship between external dependence and system resilience.

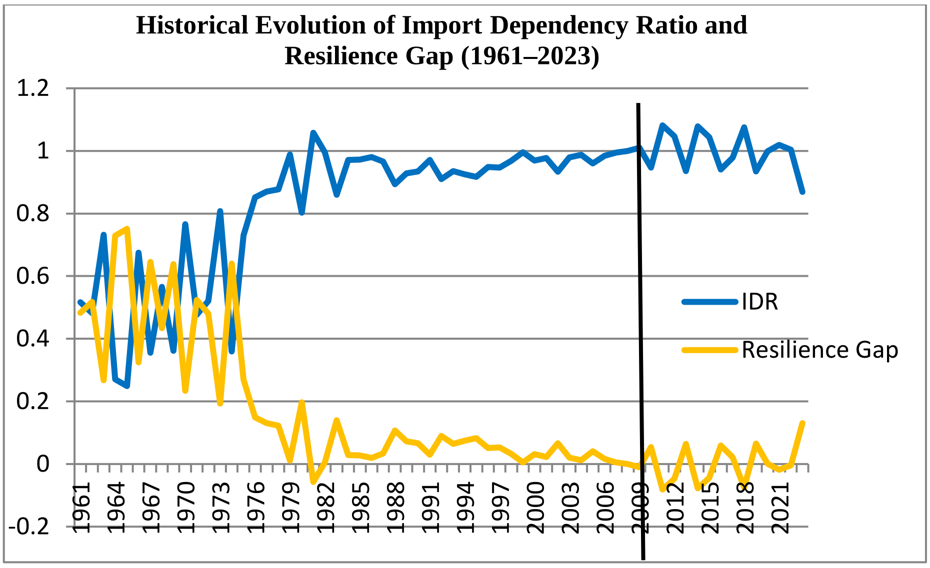

Figure 2. Historical Evolution of Import Dependency Ratio (IDR) and Resilience Gap in Jordan (1961–2023)

The early period (1960s–early 1970s) is characterized by significant fluctuations reflecting an unsettled structural base. From the mid-1970s onward, a clear directional shift emerges: the IDR rises steadily while the Resilience Gap narrows, indicating deepening dependence alongside weakening absorptive capacity. By the late 1970s and into the 1980s, the IDR stabilizes near unity while the Resilience Gap approaches—and occasionally crosses—zero, marking a transition into structurally high dependence with minimal resilience buffer. This pattern persists post-2000, with near-complete import reliance and consistently low resilience. The vertical line at 2010 denotes a methodological revision in FAO data rather than a structural economic break, as the underlying trend is unaffected.

While these trends confirm that import-dependent systems face elevated exposure to external shocks (Headey & Fan, 2008), static analysis cannot reveal the role of volatility in amplifying that exposure—the dimension the DRI is designed to capture.

4.1.2 Dynamic Analysis: The DRI

The DRI extends the static picture by incorporating both import dependence and its temporal variability, revealing patterns of latent vulnerability obscured by aggregate trends.

In the early period (1961–mid-1970s), positive DRI values largely reflected low import dependence rather than genuine structural resilience. From the late 1970s onward, the index declined sharply as dependence and volatility increased, turning negative in the early 1980s and remaining near zero or below for most subsequent periods. Although temporary improvements emerged during 2000–2008, resilience remained fragile, with recurring vulnerability reappearing after the 2008 crisis and persisting post-2010 despite data adjustments.

Overall, the DRI shows that apparent stability in import dependence can conceal vulnerability driven by the interaction between exposure and instability. This finding is consistent with evidence that global disruptions amplify volatility and intensify shock transmission in import-dependent economies (Headey & Fan, 2008; Gilbert & Morgan, 2010), particularly under conditions of trade concentration and post-2020 market instability (Kumar et al., 2024; Chaturvedi, 2024; FAO et al., 2025).

4.1.3 Annual Decision Matrix and Policy Interpretation

To translate the DRI into an operational tool, annual food system conditions are classified into four resilience levels—Relatively Safe, Alert, Warning, and Critical. The classification thresholds were derived from the empirical distribution of DRI values within the Jordanian sample and are intended to provide a context-specific framework rather than universal food security benchmarks. This approach enables the decision matrix to distinguish between relatively stronger and weaker resilience conditions over time while remaining consistent with the study's objective of monitoring structural changes in vulnerability rather than establishing internationally comparable resilience standards. Table 2 presents the full annual classification for Jordan.

Table 2. Annual Classification of Food System Resilience in Jordan (1961–2023)

Resilience Level	**Years**
Relatively Safe	1963, 1964, 1965, 1966, 1967, 1968, 1969, 1971, 1972, 1974, 1975
Alert	1970, 1973, 1976, 1977, 1978, 1980, 1983, 1988, 1989, 1990, 1992, 1993, 1994, 1995, 1997, 2002, 2010, 2013, 2016, 2019, 2023
Warning	1961, 1962, 1979, 1982, 1984, 1985, 1986, 1987, 1991, 1996, 1998, 1999, 2000, 2001, 2003, 2004, 2005, 2006, 2007, 2008, 2017, 2020
Critical	1981, 2009, 2011, 2012, 2014, 2015, 2018, 2021, 2022

Relatively Safe years are confined almost entirely to the early 1960s and early 1970s—periods of lower structural dependence. The majority of the sample falls within Alert and Warning, with Critical episodes clustering around the 1981 crisis and the post-2008 period. This distribution confirms that vulnerability in Jordan is structural rather than episodic: risk is not driven primarily by discrete shocks but by the chronic interaction between high dependence and market instability.

As an early warning instrument, the matrix enables timely identification of resilience deterioration and supports targeted policy responses calibrated to the severity of each condition. This operationalization reflects the broader view that food system vulnerability is shaped not only by the level of import dependence but by its stability under external pressure—and that trade can function as either a stabilizing or destabilizing force depending on risk management capacity (Clapp, 2017; Timmer, 2010).

4.2 Econometric Analysis

4.2.1 Unit Root Tests

Stationarity was assessed using the Augmented Dickey–Fuller (ADF) test. Results (Table 3) indicate a mixed integration order: DRI is stationary at level I(0), while IDR and the transformed volatility variable (VOL2) are stationary at first difference I(1). The original volatility measure (VOL) is integrated of order I(2) and is excluded from estimation; VOL2 satisfies the ARDL requirement that no variable exceed I(1).

Table 3. Unit Root Test Results (ADF)

Variable	Level (p-value)	First Difference	Order of Integration
IDR	0.578	0.000	I(1)
DRI	0.035	—	I(0)
VOL2	0.260	0.000	I(1)

The mixed integration order confirms the appropriateness of the ARDL framework, which accommodates I(0) and I(1) variables within a unified estimation structure.

4.2.2 ARDL Estimation and Long-Run Coefficients

Based on the Akaike Information Criterion, the optimal specification is ARDL(2,3,4). Model diagnostics confirm a good fit: the F-statistic is significant, R^2 is relatively high, and the Durbin–Watson statistic is close to 2, indicating no serial correlation in the baseline specification.

Table 4. ARDL Long-Run Estimation Results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
IDR	−0.868	0.014	−60.883	0.000
VOL2	−0.156	0.038	−4.055	0.002
C	0.824	0.125	6.577	0.000

Both coefficients are negative and statistically significant, indicating that lower resilience values are systematically associated with higher levels of import dependence and greater instability in import dependence. The IDR coefficient ($\beta = -0.868$, $p < 0.01$) exhibits the largest magnitude within the estimated resilience framework, while the VOL2 coefficient ($\beta = -0.156$, $p < 0.01$) indicates that instability is also closely associated with lower resilience outcomes.

Because the Dynamic Resilience Index (DRI) is constructed using both IDR and VOL2, these estimates should be interpreted as reflecting the relative contribution and dynamic association of the underlying resilience dimensions rather than fully independent causal effects. In this context, the larger magnitude of the IDR coefficient suggests that structural dependence constitutes the dominant component within the observed resilience framework, whereas volatility further amplifies vulnerability beyond dependence levels alone.

When major global shocks (2008, 2020, and 2022) are incorporated as a dummy variable, the estimated coefficient remains negative and statistically significant ($\beta = -0.0078$, $p < 0.01$), indicating that external disruptions are associated with lower resilience outcomes beyond the dependence–volatility interaction captured by the DRI framework.

4.2.3 Bounds Test for Cointegration

Table 5. Bounds Test Results

F-Statistic	Lower Bound (1%)	Upper Bound (1%)
13.164	4.61	5.56

The F-statistic (13.164) substantially exceeds the upper bound at the 1% significance level, confirming a stable long-run cointegrating relationship among DRI, IDR, and VOL2 and justifying estimation of the Error Correction Model.

4.2.4 Long-Run Relationships

Table 6. Long-Run Cointegration Results

Variable	Coefficient	t-Statistic	Prob.
IDR	−0.818	−110.99	0.000
VOL2	−0.417	−4.015	0.000

The long-run estimates are consistent with the broader resilience framework. Both IDR ($\beta = -0.818$, $p < 0.01$) and VOL2 ($\beta = -0.417$, $p < 0.01$) are negatively and significantly associated with resilience outcomes over time, indicating that structural dependence and instability remain persistent dimensions of food system vulnerability throughout the sample period.

Given that the Dynamic Resilience Index (DRI) is constructed using these underlying dimensions, the coefficients should be interpreted as long-run decomposition relationships within the resilience framework rather than as evidence of fully independent causal effects. The larger magnitude observed for volatility ($\beta = -0.417$) suggests that instability may play an increasingly important role in shaping resilience outcomes over extended horizons, particularly under conditions of repeated external disturbances.

The relatively large t-statistics should also be interpreted in light of the close structural linkage between the DRI and its constituent dimensions. Accordingly, emphasis is placed on the direction, consistency, and policy relevance of the estimated relationships rather than on statistical significance alone.

4.2.5 Error Correction Model

Table 7. Error Correction Model Results

Variable	Coefficient	t-Statistic	Prob.
ECM(−1)	−1.003	−7.499	0.000
ΔIDR	−0.868	−71.831	0.000
ΔVOL2	−0.156	−5.848	0.000

The error correction term (ECM(−1) = −1.003, $p < 0.01$) is negative and statistically significant, confirming adjustment toward long-run equilibrium. The magnitude implies near-complete correction within a single period, though the value marginally exceeding unity suggests potential overshooting—consistent with a responsive but structurally constrained system. The short-run coefficients of ΔIDR and ΔVOL2 are negative and significant, mirroring the long-run pattern and indicating that both dependence and volatility reduce resilience across time horizons. This adjustment dynamic aligns with resilience theory's emphasis on recovery capacity following external disturbances (Tendall et al., 2015).

4.2.6 Robustness and Diagnostic Tests

Table 8. Diagnostic Tests

Test	F-Statistic	Prob.
Breusch–Godfrey Serial Correlation LM	1.148	0.327
Breusch–Pagan–Godfrey Heteroskedasticity	3.309	0.002

The Breusch–Godfrey test confirms the absence of serial correlation ($p = 0.327$), validating the dynamic specification. Heteroskedasticity is detected ($p < 0.01$) and addressed through HAC (Newey–West) standard errors.

Table 9. HAC (Newey–West) Robustness Results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
IDR	−0.868	0.0167	−51.831	0.000
VOL2	−0.156	0.060	−2.594	0.013

Both coefficients retain their sign, magnitude, and significance under HAC adjustment, confirming that the estimated relationships are not an artifact of heteroskedasticity. CUSUM and CUSUM of Squares tests (Figures 3) remain within the 5% critical bounds throughout the sample period, indicating stable model parameters. Collectively, the diagnostics confirm a well-specified, robust model whose findings are both statistically reliable and structurally interpretable.

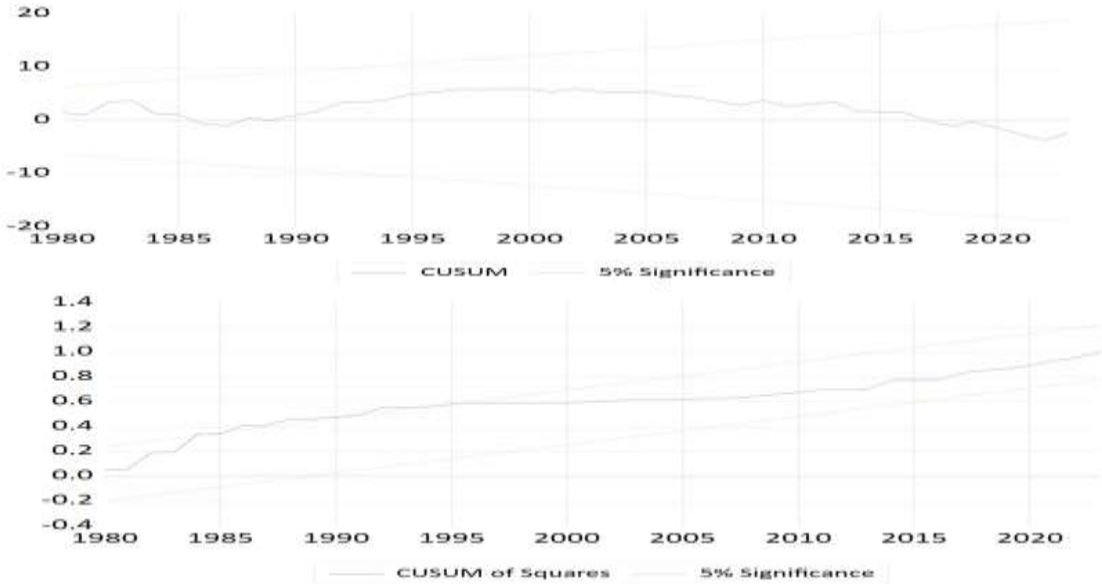

Figure 3. CUSUM and CUSUMSQ stability tests.

4.2.7 Forecasting and Scenario Analysis

To explore the potential evolution of food system resilience, forecasting and scenario analyses were conducted using the estimated ARDL framework. The forecasting exercise provides a conditional baseline projection of the Dynamic Resilience Index (DRI) under the continuation of historical structural conditions and should therefore be interpreted as an analytical projection rather than a precise prediction. It assumes no major structural breaks beyond those reflected in the historical data and is intended to support long-term resilience monitoring and policy analysis.

The scenario analysis complements the baseline forecast by examining the sensitivity of resilience outcomes to alternative structural conditions. The simulated changes in import dependence and volatility represent moderate stress conditions consistent with the historical range of variation and should be interpreted as analytical simulations rather than forecasts of actual future developments.

4.2.7.1 Baseline Forecast (2024–2030)

The baseline forecast projects a declining DRI trajectory through 2024–2027, followed by stabilization at a lower equilibrium through 2030. Widening confidence intervals over the forecast horizon reflect growing uncertainty, driven primarily by external volatility and continued exposure to global shocks.

Table 10. Baseline Forecast Results

Variable	Coefficient	Std. Error	t-Statistic	Prob.
IDR	−0.836	0.0186	−44.856	0.000
VOL2	−0.204	0.057	−3.576	0.000

Note: Forecasts based on the estimated ARDL model using HAC-adjusted standard errors.

The forecast coefficients are consistent with the main model in sign and significance. The IDR retains a strong negative effect ($\beta = -0.836$, $p < 0.01$), confirming structural dependence as the primary forward-looking driver of vulnerability. The VOL2 coefficient is marginally larger in magnitude than in the baseline estimation ($\beta = -0.204$ vs. -0.156), suggesting that instability may play an increasingly consequential role in shaping resilience dynamics over the forecast period. The stability of these relationships under a forward-looking specification reinforces the conclusion that food system vulnerability is structurally embedded rather than cyclically driven.

The relatively large t-statistics observed for some coefficient estimates should be interpreted in light of the construction of the DRI framework. Because the resilience index incorporates both import dependence and instability dimensions, part of the statistical strength may reflect the close structural linkage between the composite indicator and its underlying components. For this reason, the emphasis of the analysis is placed on the direction, consistency, and policy interpretation of the relationships rather than on coefficient significance alone.

4.2.7.2 Scenario Analysis

Three scenarios were constructed to assess the sensitivity of resilience outcomes to changes in structural conditions:

- **Baseline**: continuation of current dependence and volatility levels
- **Improvement**: 10% reduction in import dependence; 20% reduction in volatility
- **Risk**: 10% increase in import dependence; 30% increase in volatility

Table 11. Scenario Comparison

Scenario	IDR Impact	VOL Impact	Resilience Implication
Baseline	Negative	Negative	Persistent vulnerability
Improvement	Less negative	Less negative	Partial improvement
Risk	Negative	Negative (higher exposure)	Increased vulnerability

Under the improvement scenario, resilience outcomes improve measurably relative to the baseline, but negative effects persist—indicating that policy-driven reductions in dependence and volatility can attenuate but not eliminate underlying fragility. This finding is analytically significant: it suggests that vulnerability is not primarily cyclical but reflects structural features of the food system that are resistant to moderate intervention.

The risk scenario produces a further deterioration in resilience, with the system exhibiting greater sensitivity to adverse external conditions than the improvement scenario yields in gains. This asymmetry underscores the importance of volatility as a risk amplifier: adverse shocks compound existing fragility more forcefully than equivalent improvements in conditions can offset it. Across all three scenarios, the direction and relative magnitude of effects remain consistent, confirming that the interaction between dependence and instability—rather than either variable in isolation—is the central determinant of resilience outcomes.

4.2.7.3 Short-Run Dynamics

Table 12. ARDL Short-Run Estimates (HAC-Adjusted)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DRI(−1)	0.216	0.104	2.086	0.043
DRI(−2)	−0.244	0.128	−1.908	0.063
IDR	−0.866	0.016	−53.336	0.000
IDR(−1)	0.181	0.088	2.055	0.046
IDR(−2)	−0.176	0.103	−1.714	0.094

VOL2	−0.156	0.059	−2.631	0.012
VOL2(−1)	−0.082	0.037	−2.230	0.031
VOL2(−2)	−0.055	0.034	−1.600	0.117
SHOCK	−0.008	0.002	−3.213	0.003

Note: HAC (Newey–West) standard errors correct for heteroskedasticity.

The short-run estimates confirm the persistence of both primary relationships. The contemporaneous IDR effect is strongly negative and highly significant ($\beta = -0.866$, $p < 0.01$), while lagged IDR terms indicate partial offsetting adjustment over subsequent periods—consistent with a system that responds sharply to dependence increases but adjusts only gradually. Volatility exerts a negative short-run impact at the contemporaneous lag ($\beta = -0.156$, $p < 0.05$) and continues to suppress resilience at VOL2(−1), suggesting that instability effects are not absorbed within a single period. The SHOCK variable is negative and significant ($\beta = -0.008$, $p < 0.01$), confirming that major global disruptions produce immediate, measurable declines in resilience rather than operating through dependence or volatility channels alone.

4.3 Synthesis and Discussion

Taken together, the empirical findings indicate that food system vulnerability in Jordan is more complex than suggested by conventional static indicators. Although aggregate IDR trends indicate relative stability during the later years of the study period, the DRI consistently identifies underlying fragility, particularly during and after major global disruptions. These findings demonstrate that resilience depends not only on the level of import dependence but also on its stability under external shocks.

A key finding is the independent role of volatility. Across the long-run, short-run, and scenario analyses, instability in import dependence consistently reduces resilience even when average dependence changes little. The larger long-run coefficient for VOL2 ($\beta = -0.417$) compared with its short-run effect indicates that the adverse consequences of instability accumulate over time. This suggests that policies aimed at reducing volatility may strengthen resilience more effectively than those focusing solely on lowering average import dependence.

The estimated shock variable reinforces this interpretation. The 2008 food crisis, the COVID-19 pandemic, and the geopolitical disruptions of 2022 intensified pre-existing structural vulnerabilities rather than creating only temporary disturbances. Consistent with these findings, the scenario analysis indicates an asymmetric risk structure in which adverse shocks increase vulnerability more strongly than favourable conditions restore resilience, supporting precautionary rather than reactive policy responses.

The results also contribute to the resilience literature by showing that vulnerability in import-dependent food systems is a dynamic property arising from the interaction between external exposure and instability rather than a fixed consequence of resource constraints (Tendall et al., 2015; Béné et al., 2016). They are consistent with previous evidence linking market instability to food system fragility (Anderson & Nelgen, 2012; Headey & Fan, 2008; Gilbert & Morgan, 2010) while extending this literature through the Dynamic Resilience Index (DRI), an integrated framework for monitoring resilience dynamics.

Overall, the empirical evidence supports the study hypotheses, demonstrating that higher import dependence, greater instability, and major global shocks are associated with lower food system resilience and highlighting the need to address both dependence and instability simultaneously in resilience-oriented policy design.

5. CONCLUSION

The findings demonstrate that food system resilience in Jordan is best understood as a dynamic process rather than a static condition. Resilience is shaped by the interaction between import dependence, the stability of that dependence, and exposure to external shocks, indicating that these dimensions should be considered jointly when assessing food system vulnerability.

A key finding is that instability in import dependence represents a critical dimension of resilience. Even when average dependence remains relatively stable, greater volatility is associated with increased vulnerability, highlighting the importance of maintaining stability as well as reducing dependence in resilience-oriented policies.

The analysis further shows that major global disruptions intensified existing structural vulnerabilities rather than creating isolated disturbances, underscoring the need to evaluate resilience within a broader structural and external context.

Methodologically, the Dynamic Resilience Index (DRI) provides an integrated quantitative framework for capturing the interaction between dependence and instability within a single resilience measure. The proposed framework offers a practical tool for monitoring vulnerability in import-dependent economies and supports more dynamic approaches to resilience assessment.

Future research may extend this framework by incorporating alternative measures of volatility and applying the DRI across a wider range of country settings to evaluate its broader applicability and external validity.

6. POLICY IMPLICATIONS

The findings indicate that food system resilience in Jordan is constrained not only by high import dependence but also by instability in that dependence. Accordingly, food security policy should move beyond traditional self-sufficiency objectives toward a dual strategy that simultaneously reduces external exposure and strengthens system stability.

Diversifying import sources through long-term trade agreements can reduce concentration risk, while strategic grain reserves and appropriate risk-hedging instruments can help moderate supply disruptions during periods of external instability. Domestic policy should likewise prioritize targeted investments in climate-resilient and productivity-enhancing agricultural practices rather than broad production expansion, given Jordan's resource constraints.

In addition, incorporating the Dynamic Resilience Index (DRI) into early warning systems would enable policymakers to identify rising vulnerability and respond proactively before external shocks translate into more severe food security risks. Overall, the findings highlight that managing instability in import dependence is as important as reducing dependence itself for strengthening long-term food system resilience.

7. LIMITATIONS

The findings should be interpreted in light of several limitations. First, the analysis relies on FAO Food Balance Sheets, which include partial estimations and a post-2010 methodological revision, although the use of relative indicators mitigates comparability concerns. Second, the Dynamic Resilience Index (DRI) focuses on import dependence and its stability and therefore does not capture other dimensions of food security, such as purchasing power, governance quality, institutional capacity, or supply-chain resilience. Third, the decision-matrix thresholds are specific to the Jordanian context and may not be directly transferable to other countries.

Because the DRI is constructed from the Import Dependency Ratio (IDR) and the volatility measure (VOL2), a degree of mechanical association exists between the composite index and its components. Accordingly, the econometric analysis should be interpreted as assessing the dynamic consistency of the proposed resilience framework rather than establishing fully independent causal relationships. Furthermore, although the ARDL–ECM framework captures both long- and short-run dynamics, it identifies statistical associations rather than strict causality. Future research could strengthen the framework through alternative volatility measures, structural models (e.g., VAR/SVAR), and cross-country validation.

8. FUTURE RESEARCH

Future research may extend this framework by incorporating country-specific shocks to better capture the interaction between domestic instability and global vulnerability. Additional work may also evaluate alternative representations of volatility, including rolling standard deviations, GARCH-family models, and regime-switching approaches, to determine whether different measures of instability generate similar resilience patterns and provide deeper insights into nonlinear food system dynamics. Expanding the analysis to cross-country settings and integrating sector-specific food shocks would further enhance understanding of the structural drivers of food system resilience and the broader applicability of the proposed framework.

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