Title: Key Agricultural Supply Risks for Global Poverty and Undernourishment: A Systematic Risk Profiling Approach

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Abstract

The intersection of agricultural production shocks—ranging from climate-induced yield failures to conflicts and policy responses—can trigger systemic volatility similar to the 2008 agrifood crisis. Standard Computable General Equilibrium (CGE) assessments typically rely on discrete deterministic counterfactuals that fail to capture the complex, correlated nature of real-world risk factors. This paper addresses a critical gap: How does the complex landscape of agricultural shocks shape global poverty and undernourishment? We propose a framework to move from isolated scenario analysis to a probabilistic "risk map" of global poverty using the Systematic Risk Profiling (SRP) method (Mukashov et al., 2026). Our approach relies on three pillars. Pillar 1: Monte Carlo Simulations. Utilizing historical data, we generate 10,000 large-scale Monte Carlo simulation scenarios of global agricultural production shocks across key global agricultural producers and vulnerable Global South regions. Pillar 2: Microsimulation Integration. We link the global CGE model with continuous household poverty and undernourishment microsimulation modules to dynamically update regional estimates. Pillar 3: Machine Learning for Risk Attribution. We employ Random Forest regression (Permutation Importance) to estimate the relative importance of sampled agricultural shocks on household welfare outcomes worldwide.

1. Introduction

The standard paradigm in global food security analysis assumes a highly integrated transmission mechanism where volatility in global food markets (e.g., wheat, rice) directly dictates global poverty outcomes. Following the 2007-2008 food crisis, empirical and structural models have frequently explored these impacts. At the global level, Computable General Equilibrium (CGE) models remain the standard tool for such macroeconomic assessments.

However, standard global CGE assessments exhibit two major limitations. First, they typically focus on aggregate macroeconomic trade and sectoral shifts rather than detailed household-level welfare. Flagship databases and models (e.g., standard GTAP) lack endogenous household disaggregation by income level, precluding direct poverty and undernourishment estimation. Second, assessments usually rely on deterministic counterfactual scenarios. As a result, the true probability distributions and tail risks of severe events—such as the scale and likelihood of increased undernourishment in the Global South—are rarely quantified.

This paper addresses these gaps. While many qualitative vulnerabilities in the global agrifood system are well-documented in the literature (e.g., MENA's reliance on imported wheat or the importance of domestic staples in Africa), this study is the first to systematically quantify their exact probability distributions and relative importance within a fully integrated global general equilibrium framework.

We introduce two methodological extensions. First, utilizing the GLOBE CGE model (Thierfelder, 2021), we structurally decompose households by income quintiles and link endogenous changes in household consumption and national food supply directly to continuous global poverty and undernourishment modules. Second, we apply the Systematic Risk Profiling

(SRP) methodology (Mukashov et al., 2026) to track the propagation of historical agricultural production shocks.

By subjecting the integrated CGE-microsimulation system to 10,000 correlated Monte Carlo shocks, we generate a comprehensive dataset of economic outcomes, including poverty and undernourishment distributions. We then employ machine learning—specifically Permutation Random Forest regression—to trace the variance of these outcomes back to their exogenous origins.

The resulting risk decomposition validates classical trade theory while revealing distinct structural shifts in global vulnerability. As expected, the model quantifies high exposure of import-dependent regions to staple volatility in the Black Sea and North America. However, the machine learning attribution also refines the traditional narrative that global staples universally dictate extreme poverty and undernourishment. We identify three distinct transmission mechanisms: (1) In Sub-Saharan Africa, extreme poverty and undernourishment remains statistically insulated from global wheat and rice prices, driven instead by localized, non-tradable root crops and coarse grains; (2) In transitioning Asian economies, vulnerability has now includes foreign feed (South American oilseeds) due to the expansion of the livestock and aquaculture sectors; and (3) In export-dependent tropical regions, extreme poverty and undernourishment can also be triggered by yield failures in non-edible cash crops that force real exchange rate depreciations and import broad-based inflation.

2. Methodology

Our methodological framework balances computational intensity with empirical realism. The primary objective is to exhaustively cover the joint probability space of major agricultural production shocks and rigorously trace their transmission mechanisms down to localized, highly vulnerable populations. The framework is built upon three pillars: structural model engineering, stochastic scenario generation, and machine learning risk attribution.

2.1. Pillar 1: Building the SAM, CGE Model Engineering, and Microsimulation Linkage

The macroeconomic core of the analysis utilizes the GLOBE CGE model calibrated to the latest GTAP v12 database (reference year 2023). We employ a strategic regional aggregation that distinguishes between global "Agricultural Powerhouses" (major price-setting exporters) and "Poverty-Stricken Regions" (vulnerable importers or low-income subsistence economies).

Table 1: Regional Aggregation in the GLOBE Model (19 regions)

Code	Name	Description	Economic Role in Model
NAmer	North America	US and Canada	Primary price-setter for global staple grains.
Braz	Brazil	Brazil	Global powerhouse for soy, meat
Argt	Argentina	Argentina	Key exporter of soy products and wheat.
LatAm	Rest of Latin America	Mexico, Central America, Caribbean, Rest of South America	Diverse block of net agricultural importers.
Eur	European Union +	EU, UK, EFTA, Balkans	High-income block with major ag-subsidies.
FSU	Russia+	All former Soviet Union countries	The "Black Sea" grain hub.
China	China	China (Mainland, HK, Macao)	Largest global consumer; demand drives global prices.
India	India	India	Swing player in global rice and wheat markets.
RSAsia	Rest of South Asia	Pakistan, Bangladesh, Nepal, Sri Lanka, Afghanistan	Low-income region dependent on food imports.
Indo	Indonesia	Indonesia	Dominant player in the global vegetable oil complex.
ThaiViet	Thailand & Vietnam	Thailand and Vietnam	Sets the global benchmark price for rice.
RoSEAsia	Rest of SE Asia	Malaysia, Philippines, Rest of SE Asia	Mixed economy of net rice importers and palm oil exporters.
RichAsia	Rich Asia	Japan, South Korea, Taiwan, Singapore	High-income, net food-importing nations.
AusNZ	Australia & New Zealand	Australia and New Zealand	Counter-seasonal suppliers of wheat, meat, and dairy.
MENA	All MENA	Middle East, North Africa, Turkey	World's largest net importing block for wheat.
WAfr	West Africa	Nigeria, Ghana, Ivory Coast, Senegal, ECOWAS	High-poverty region dependent on root crops and imported rice.
CAfr	Central Africa	DRC, Cameroon, ECCAS	Subsistence agriculture (roots/tubers) and high extreme poverty.
EAfr	East Africa	Ethiopia, Kenya, Tanzania, Uganda, Sudan, Somalia	Dependent on maize and rainfed agriculture; food insecurity hotspot.
SAfr	Southern Africa	South Africa, Angola, Zimbabwe, Zambia, Mozambique	Mix of commercial and subsistence farming relying on maize.

To capture the transmission of shocks throughout the entire economy, the model maps 27 distinct sectors. While the entire industrial and service economy is modeled to ensure macroeconomic closure, the primary edible agricultural sectors (Grains, Other Crops, Livestock, and Fishing) serve as the focus for the stochastic supply shocks.

Table 2: Sectoral Aggregation

Code	**Description**	**Content & Economic Role**
Rice	Rice	Integrated sector covering paddy and milled rice.
Wheat	Wheat	Primary tradable staple grain.
OthGrain	Other Grains	Maize, sorghum, millet, barley.
VegFruit	Vegetables & Fruits	Vegetables, fruits, nuts, roots, tubers, pulses.
OilSeed	Oil Seeds	Soybeans, groundnuts, palm, sunflower, rapeseed.
CashCrops	Cash Crops	Sugar, cotton, coffee, tea, cocoa, spices, rubber.
Livestock	Livestock	Live animals, raw milk, eggs, wool.
Fishing	Fishing	Marine and freshwater fishing and aquaculture.
Forestry	Forestry	Forestry products.
MiningEn	Energy Mining	Extraction of coal, crude oil, and natural gas.
MiningOt	Other Mining	Mining of metal ores and other minerals.
MeatProc	Processed Meat	Meat processing, preserving, and packing.
VegOil	Processed Veg Oil	Manufacture of crude and refined vegetable oils and fats.
Dairy	Processed Dairy	Manufacture of dairy products.
ProcFood	Other Processed Food	All other processed food manufacturing
OagProc	Non-Food Agro-Industry	Textiles, wearing apparel, leather products, wood products, paper products, and publishing.
RefFuel	Refined Fuels	Petroleum refineries and coke oven products.
Chemical	Chemicals	Basic chemicals, fertilizers, plastics, and rubber products.
MetMin	Metals and Minerals	Mineral products n.e.c. (cement, glass), ferrous metals, metals n.e.c., and metal products.
Omanuf	All Other Manufacturing	Computers, electronic and optical products, electrical equipment, machinery, motor vehicles, and transport equipment.
Construct	Construction	Building and civil engineering construction.
Utilities	Utilities	Production and distribution of electricity, gas, and water; waste management.
Trade	Trade	Wholesale and retail trade.
HtlRest	Hotels & Restaurants	Accommodation, food, and services.
Transport	Transport	Land, water, and air transport; warehousing and support activities.
OtherPrSe	Private Services	Finance, insurance, real estate, business services, and communications.
Public	Public Services	Public administration, defense, education, human health, and social work.

Household Disaggregation Strategy:

Standard global databases lack detailed household income stratification. To bridge this gap, we implemented a structural decomposition of the GTAP households. For vulnerable regions, we utilized statistical distance metrics (Kullback-Leibler Divergence and Wasserstein distance) across household survey data to identify specific countries whose internal distributions most accurately represent their broader regional probability density functions. We then leveraged detailed, recent national SAMs (primarily from IFPRI and WIDER) to extract precise income and expenditure shares and used cross-entropy SAM balancing methods to split households into 5 quintiles in key regions.

Table 3: Representative SAM Selection for Household Income and Consumption Decomposition

GLOBE_REG	Description	Representative Country	Source for Decomposition
LatAm	Rest of Latin America	Colombia	IFPRI SAM 2016
China	China	China	IFPRI SAM 2024
India	India	India	IFPRI SAM 2022
RSAsia	Rest of South Asia	Bangladesh	IFPRI SAM 2022
Indo	Indonesia	Indonesia	IFPRI SAM 2022
ThaiViet	Thailand & Vietnam	Vietnam	IFPRI SAM 2022
RoSEAsia	Rest of SE Asia	Philippines	IFPRI SAM 2023
MENA	Middle East & North Africa	Jordan	IFPRI SAM 2016
WAfr	West Africa (ECOWAS)	Nigeria	IFPRI SAM 2022
CAfr	Central Africa (ECCAS)	DRC	IFPRI SAM 2022
EAfr	East Africa (EAC+)	Ethiopia	IFPRI SAM 2022
SAfr	Southern Africa (SADC)	South Africa	WIDER SAM 2019

Dynamic Microsimulation Linkage

To translate aggregate macroeconomic shocks into localized human impacts, we employ a top-down microsimulation architecture that links endogenous CGE outcomes with region-specific, continuous probability density functions (PDFs). This allows us to capture the highly asymmetrical, non-linear welfare dynamics at the tails of the distribution.

- **Poverty:** Base-year welfare distributions are reconstructed using detailed percentile-level data from the World Bank's Poverty and Inequality Platform (PIP). We apply Kernel Density Estimation (KDE) to these 100-point distributional datasets to generate continuous, infinite-precision welfare density functions for each region. Endogenous changes in real consumption generated by the CGE model—explicitly stratified by household income quintile—are applied to horizontally shift the respective segments of the welfare curve. We then calculate the definite integral of the updated Cumulative

Distribution Functions (CDFs) up to the 2021 PPP international poverty lines (e.g., $3.00 and $4.20/day) to estimate the new exact headcount ratios.

- **Prevalence of Undernourishment (PoU):** The food security module maps CGE agricultural supply outcomes to the FAO's probability distribution framework. Baseline caloric intake is modeled as a continuous log-normal distribution, parameterized by regional mean dietary energy supply and historical inequality of access. Using baseline regional dietary caloric shares, endogenous CGE sectoral volume changes are aggregated to calculate a total caloric supply shock. To capture the non-linear emergence of hunger, this aggregate multiplier is applied to shift the Minimum Dietary Energy Requirement (MDER) threshold across the static log-normal density function, yielding the updated regional PoU.

2.2. Pillar 2: Agricultural Shock Scenarios

To generate the global agricultural production scenarios, we utilize historical FAO agricultural production value data. We apply a Hodrick-Prescott (HP) filter to separate long-term productivity trends from yield volatility. This yields historical variance estimates for the primary agricultural and livestock sectors across the 19 regions.

To preserve the empirical, cross-border climatic and economic relationships between global crop yields (e.g., the probability of simultaneous weather shocks across hemispheres), we construct a global pairwise correlation matrix of these historical deviations. This matrix is mathematically adjusted to enforce positive definiteness, a necessary condition for valid multivariate sampling. Utilizing Latin Hypercube Sampling (LHS) over a multivariate normal distribution, we draw 10,000 joint stochastic supply shocks. Finally, to ensure macroeconomic plausibility and maintain solvability within the CGE framework, the probability distributions are explicitly truncated at 75%.

2.3. Pillar 3: Machine Learning Risk Attribution

Traditional uncertainty analysis in structural economic modeling faces a fundamental decomposition dilemma: standard post-simulation importance metrics (such as standardized regression coefficients) yield biased results when exogenous input shocks are correlated. Consequently, researchers must typically choose between assuming unrealistic independence among shocks to identify key drivers, or modeling realistic correlations while forfeiting the ability to attribute the resulting economic volatility back to specific sources.

To resolve this limitation, we apply the metamodeling approach of the Systematic Risk Profiling (SRP) framework introduced by Mukashov et al. (2026) . Following their methodology, we treat the 10,000 simulated CGE outcomes as a dataset to emulate the structural relationships of the CGE model. Crucially, this approach relies on *marginal variance decomposition*, which remains statistically valid for uncertainty analysis even when input structures are highly correlated.

Specifically, we utilize Random Forest regression (RF-CART) to capture the complex, non-linear interactions between compounding supply shocks and endogenous welfare outcomes. To quantify the specific contribution of each shock to total outcome variability, we calculate robust variable importance metrics. While the original SRP framework evaluates multiple parametric and non-parametric importance metrics (including the Lindeman-Merenda-Gold method), our primary attribution here relies on Random Forest Permutation Importance (%IncMSE). By scrambling out-of-bag predictors, this non-parametric metric effectively bypasses the correlated redundancy of compound events (e.g., simultaneous regional droughts). This allows us to explicitly isolate and rank the relative importance of individual global and domestic shocks in driving extreme poverty and undernourishment.

3. Results

The Decoupling of Food Security

The integration of 10,000 Monte Carlo simulations with machine learning risk attribution provides a dual-lens view of global food security: the absolute scale of regional vulnerability (from the CGE-microsimulation outcome distributions) and the structural origins of that vulnerability (from the Random Forest Permutation Importance).

The results reject the traditional "staple monopoly" narrative. Global vulnerability is not a monolithic response to global wheat and rice markets; it is highly bifurcated into distinct, structurally isolated transmission mechanisms.

Figure 1: Distribution of Shocks: Private Consumption

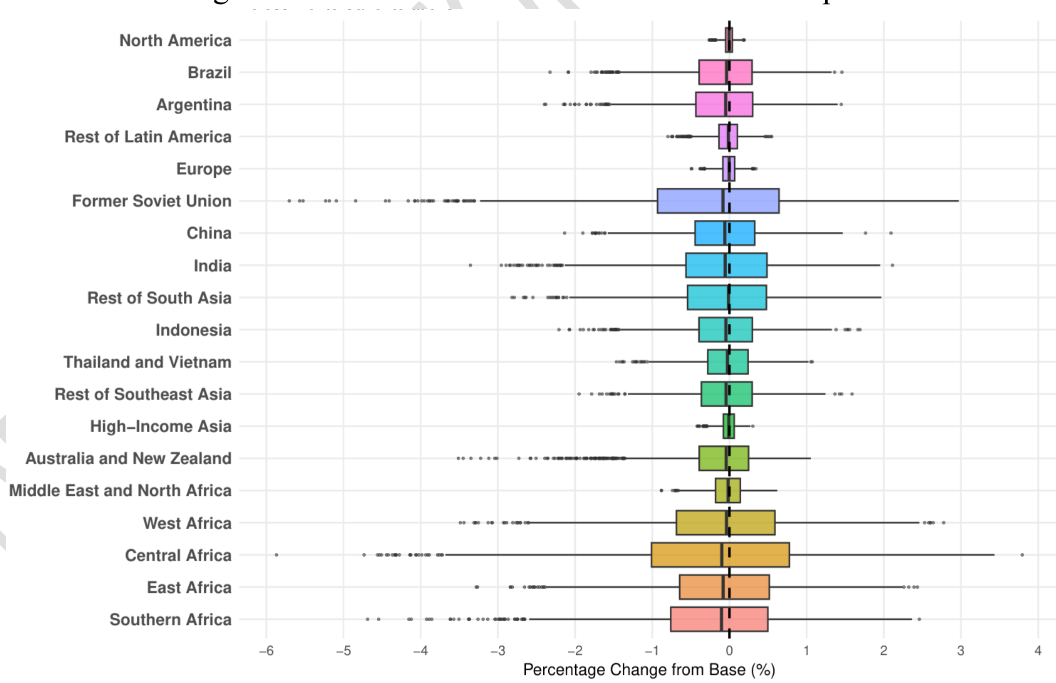


Figure 2: Distribution of Shocks: Extreme Poverty (Below $3.00)

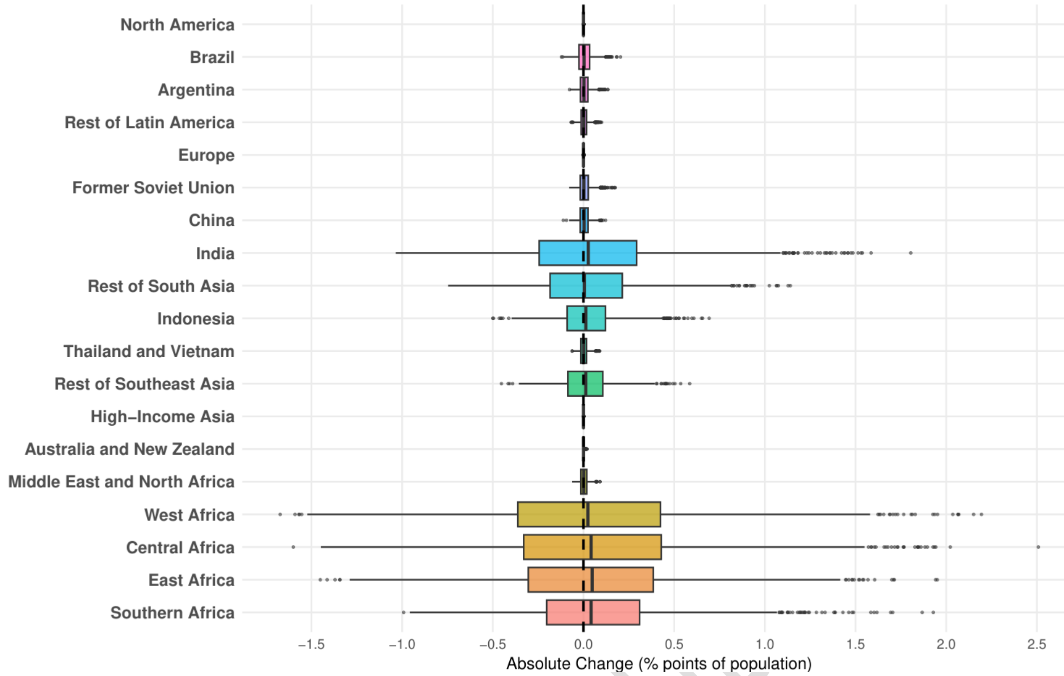
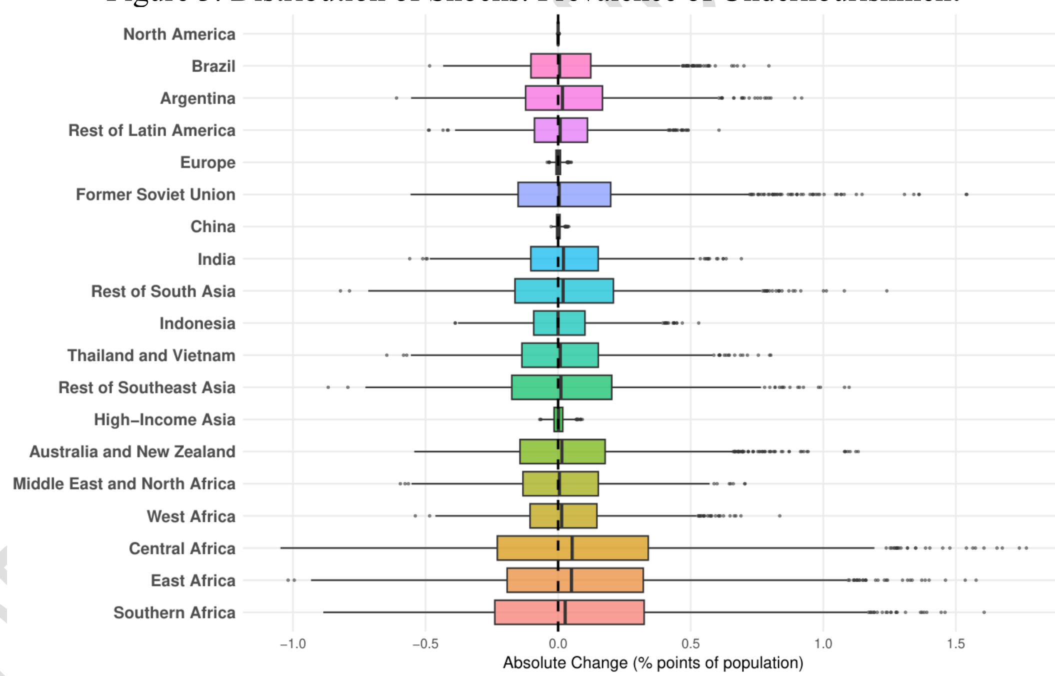


Figure 3: Distribution of Shocks: Prevalence of Undernourishment



3.1. Volatility Scaling and the Macro-Micro Transmission

The outcome distributions reveal stark geographical inequalities in baseline resilience. While macro indicators like Private Consumption experience relatively broad volatility across all regions globally (frequently swinging ±5% to ±10% from the base), the resulting impacts on human welfare are highly concentrated.

The absolute variance in Extreme Poverty (Below $3.00) and the Prevalence of Undernourishment is overwhelmingly concentrated in South Asia (India, Rest of South Asia) and Sub-Saharan Africa (West, Central, East, and Southern Africa). In these regions, shocks translate into multi-percentage-point shifts in the total population falling below survival thresholds, whereas high-income and highly integrated export regions (North America, Europe, Brazil) show near-zero absolute volatility at the extreme poverty lines.

By decomposing the residual variance of these outcomes into aggregated domestic versus foreign structural drivers, three distinct vectors of global poverty contagion emerge.

3.2. The Autarkic Core (India and South Asia)

Despite deep integration into certain global trade flows, the massive absolute volatility in South Asian poverty and undernourishment is dictated almost entirely by domestic staple isolation.

India exhibits some of the widest interquartile ranges for both Extreme Poverty and PoU. However, the Random Forest decomposition demonstrates that this variance is heavily shielded from foreign staple fluctuations. The predictive variance for extreme poverty in India is overwhelmingly dominated by domestic factors, with domestic rice, roots and vegetables, and livestock emerging as the primary structural drivers. Similarly, India's undernourishment variance is anchored almost entirely by domestic wheat and rice.

While foreign shocks occasionally penetrate the region, South Asia effectively acts as an autarkic giant where localized staple yields are the absolute determinant of the poverty headcount.

Table 4: The Autarkic Core – Structural Drivers of Extreme Poverty ($3.00/day)

Region	Volatility Scale	Primary Domestic Drivers
India	High	Domestic Rice (45.2%), Domestic Roots/Veg (11.4%), Domestic Livestock (7.9%)

Rest of South Asia	High	Domestic Rice (38.5%), Domestic Cash Crops (11.0%), Domestic Livestock (9.3%)

3.3. The Subsistence Shield (Sub-Saharan Africa)

A parallel dynamic exists in Sub-Saharan Africa, though anchored by entirely different crops. Traditional aggregate trade models emphasize African macroeconomic vulnerability to global wheat prices. However, the machine learning decomposition demonstrates that extreme poverty in West, Central, and East Africa is statistically decoupled from the global grain trade.

The variance in extreme poverty is overwhelmingly driven by the aggregate sum of domestic shocks. The poorest quintiles operate in a largely non-tradable dietary economy dominated by domestic root crops (cassava and yams) and coarse grains (sorghum and millet). In Central Africa, the explicit modeling of the fisheries sector reveals that artisanal inland and coastal fishing acts as an equal structural baseline for survival alongside root crops.

Table 5: The Subsistence Shield – Structural Drivers of Extreme Poverty ($3.00/day)

Region	Volatility Scale	Primary Domestic Drivers
West Africa	High	Domestic Roots/Veg (18.1%), Domestic Coarse Grains (9.9%), Domestic Rice (5.6%)
Central Africa	High	Domestic Fishing (9.0%), Domestic Roots/Veg (9.0%), Domestic Oilseeds (5.9%)
East Africa	High	Domestic Roots/Veg (8.9%), Domestic Coarse Grains (7.7%), Domestic Cash Crops (7.0%)

3.4. The Protein Contagion (Transitioning Asia)

In transitioning economies such as Thailand, Vietnam, and China, the attribution map reveals a fundamental structural shift from *food* vulnerability to *feed* vulnerability. While absolute poverty volatility is lower here than in Sub-Saharan Africa, the transmission mechanisms are highly globalized.

As diets transition toward meat consumption, the massive Asian pork, poultry, and aquaculture sectors become structurally tethered to imported feed. The Random Forest captures this cross-border contagion effect precisely. While domestic rice remains the leading factor, South American soybean shocks emerge as a top-five structural driver for both undernourishment and extreme poverty in Thailand and Vietnam. A yield failure in foreign soy spikes feed input costs across Asia, driving up the domestic consumer price index for protein and contracting the private consumption of the urban poor.

Table 6: The "Protein Contagion" – Drivers of Undernourishment

Region	Top Domestic Drivers	Top Foreign Drivers
Thailand & Vietnam	Domestic Rice (15.4%), Domestic Cash Crops (5.9%), Domestic Roots/Veg (4.2%)	Brazilian Oilseeds (4.0%)
China	Domestic Roots/Veg (6.2%), Domestic Rice (6.1%), Domestic Livestock (5.6%)	European Fishing (2.8%)

3.5. The Cash Crop Curse: Exchange Rate Contagion

Finally, the decomposition highlights that physical food shortages are not the only vector for undernourishment. For export-dependent tropical regions, macroeconomic contagion originating in non-edible agricultural sectors severely destabilizes private consumption and, consequently, poverty rates.

In East Africa, domestic cash crops act as severe macroeconomic destabilizers, heavily driving agricultural export variance, which sequentially triggers fluctuations in the prevalence of undernourishment and private consumption. Similarly, in West Africa and Latin America, domestic cash crops are primary drivers of real exchange rate volatility. Yield failures in non-edible agriculture lead to collapses in foreign exchange generation, forcing real exchange rate depreciations. This devaluation imports massive inflation across the entire commodity basket, driving down private consumption and pushing vulnerable quintiles below the poverty line without a single domestic food crop failing.

4. Conclusion

(To be expanded for final submission)

By integrating CGE modeling with machine learning risk profiling, we demonstrate that the vectors for cross-border poverty contagion are no longer direct staple shortages, but rather indirect macroeconomic choke-points: the global feed-meat nexus, localized subsistence roots, and current account volatility driven by cash crops. Future policy interventions and trade monitoring systems must account for this structural segmentation.

References

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