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Leveraging AI Forecasting to Quantify Tariff-Induced Food Price Volatility in Net-Importing Nations

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ABSTRACT

As global trade tensions and protectionist policies intensify, net food-importing nations face heightened exposure to tariff-induced food price volatility, threatening their economic stability and food security. This study investigates the application of artificial intelligence (AI) forecasting models to quantify and predict the impacts of international tariff shocks on staple food prices in import-dependent economies. Starting from a macroeconomic perspective, the paper examines the mechanisms through which tariffs imposed by major exporters often on wheat, rice, maize, and soybean transmit price shocks across global and regional supply chains, disproportionately affecting vulnerable economies with limited domestic production capacity. The research employs machine learning algorithms, including recurrent neural networks (RNN), long short-term memory (LSTM) networks, and ensemble methods, to analyze large-scale datasets of historical trade flows, tariff adjustments, and food price indices. These models are calibrated to detect non-linear relationships and dynamic lag effects between tariff events and retail-level price inflation in developing nations. The results reveal distinct patterns of temporal volatility, with AI models outperforming traditional econometric methods in forecasting both short- and medium-term price shifts. The study further explores how AI forecasting can inform adaptive policy responses, such as buffer stock management, import diversification, and real-time subsidy allocation, to mitigate consumer-level impacts. Through country-specific case studies including those of Egypt, Bangladesh, and Kenya the analysis illustrates how predictive analytics can empower governments to design proactive, evidence-based food security interventions. Ultimately, the paper underscores the transformative role of AI in translating complex trade dynamics into actionable insights, offering a strategic tool for managing the risks of a volatile global trade environment.

Keywords: AI forecasting, Food price volatility, Tariff shocks, Net-importing countries, Machine learning, Food security policy

1. INTRODUCTION

1.1 Background on Global Trade Instability

The global agricultural trade system has undergone major transformations in the past three decades, driven by increased liberalization, technological advancements, and multilateral agreements. These shifts enabled countries to specialize, export surpluses, and import deficit commodities to stabilize domestic food supply [1]. However, the global nature of trade also made national food systems more vulnerable to external shocks. Supply chain disruptions, climate-related crop failures, and international policy shifts have repeatedly exposed the fragility of this interconnected system.

Recent decades have witnessed episodes of severe volatility tied to geopolitical conflict, economic sanctions, and pandemics, all of which have compromised trade predictability. The COVID-19 pandemic disrupted logistics globally, triggering panic-induced export restrictions and protective trade policies that challenged the foundational assumptions of food access through international markets [2]. Trade sanctions against major exporters such as Russia and Iran further destabilized global grain and fertilizer markets [3].

Global institutions, such as the World Trade Organization (WTO) and the Food and Agriculture Organization (FAO), have warned that food security is now a critical economic risk exacerbated by geopolitical fragmentation and environmental uncertainty [4]. These disruptions have sparked renewed debates about food sovereignty, trade dependency, and the appropriate level of self-sufficiency.

Figure 1 later in this article provides a timeline of key tariff events that have affected staple crop flows since 2000. It illustrates how moments of political and economic instability have often coincided with trade interventions that altered prices, supply, and food availability in dependent nations. In such a system, any instability in trade policy has immediate and measurable implications for food security outcomes [5].

1.2 Rise of Tariff Shocks in Agricultural Trade

Among the various instruments of trade disruption, tariffs have emerged as one of the most potent and politically charged. Governments frequently impose tariffs to protect domestic producers, retaliate against adversarial trade practices, or control the outflow of vital resources [6]. While common in industrial goods, the application of tariffs to agricultural commodities is uniquely impactful due to the inelastic nature of food demand and its social importance.

Historically, import tariffs have been used to raise government revenue and safeguard local farmers from being undercut by subsidized imports. Conversely, export tariffs may be employed to keep staple food affordable domestically or to leverage geopolitical influence during crises [7]. Both actions, however, cause ripple effects across global markets, especially when implemented by top-producing countries. During the 2007–2008 food crisis, wheat and rice export tariffs by India and Vietnam triggered price escalations that impacted more than 40 importing countries [8].

In recent years, tariff events have become more frequent and less predictable, driven by nationalism, regional conflicts, and institutional breakdowns. The U.S.–China trade conflict (2018–2020) and Russia's invasion of Ukraine in 2022 both resulted in significant commodity tariff shifts that affected soybeans, maize, and wheat markets [9].

These tariff shocks often arise abruptly, leaving import-dependent nations with limited time to adjust procurement, renegotiate contracts, or substitute with alternative suppliers. Table 1 later in this article highlights nations that are most vulnerable to such events based on their dependency and exposure indices [10]. These growing shocks underscore the urgency of re-examining resilience frameworks for food-importing countries.

1.3 Net-Importing Nations and Food Security Vulnerability

Net food-importing countries, particularly those in the Global South, face compounding vulnerabilities when exposed to tariff shocks. Many of these nations rely heavily on a narrow set of trading partners for critical staple crops such as wheat, rice, maize, and soybeans. In some cases, imports account for over 70% of national consumption of certain staples, rendering them extremely sensitive to price and supply shocks originating abroad [11].

This dependency is exacerbated by structural weaknesses such as limited domestic production capacity, constrained foreign exchange reserves, and underdeveloped logistics infrastructure. When tariff shocks inflate global prices, these nations often face a triple burden: costlier imports, depreciating currency effects, and rising domestic inflation [12]. Moreover, many lack strong fiscal mechanisms such as subsidy buffers or emergency reserves to mitigate the shock's impact on vulnerable populations.

The socio-political consequences are severe. Historical analysis shows that tariff-induced food inflation has triggered protests, instability, and government transitions, particularly in fragile states [13]. The Arab Spring was preceded by a sharp rise in bread and cereal prices in countries such as Egypt and Tunisia, following global trade disturbances. For nations with high poverty rates, even modest increases in staple prices can lead to reduced caloric intake and increased malnutrition [14].

Table 1 demonstrates the distribution of import dependency and vulnerability across 20 high-risk nations. These findings emphasize the need for comprehensive modeling to understand how tariff shocks interact with local food systems and trigger broader economic and social outcomes [15].

Table 1: Top 20 Net Food-Importing Nations by Staple Crop and Vulnerability Index

Rank	Country	Cereal Import Dependency (%)	GHI Score (0–100)	FX Reserve Coverage (Months)	Tariff Vulnerability Index (1–10)
1	Yemen	88.3	45.1	1.2	9.5
2	Haiti	83.5	40.7	1.8	9.3
3	Somalia	90.1	43.5	1.1	9.2
4	Sudan	79.2	39.0	2.0	8.9
5	Liberia	81.0	35.6	1.7	8.8
6	Guinea-Bissau	77.5	36.2	1.6	8.7
7	Democratic Rep. of Congo	76.0	44.1	2.2	8.6
8	Burkina Faso	70.9	37.4	2.4	8.4
9	Afghanistan	72.5	39.8	2.5	8.3
10	Malawi	65.0	34.0	2.0	8.1
11	Sierra Leone	68.7	33.1	2.1	8.0

Rank	Country	Cereal Import Dependency (%)	GHI Score (0–100)	FX Reserve Coverage (Months)	Tariff Vulnerability Index (1–10)
12	Mozambique	67.2	32.5	2.8	7.9
13	Bangladesh	62.1	25.7	3.2	7.7
14	Chad	69.3	38.0	2.3	7.6
15	Togo	66.5	31.6	3.1	7.4
16	Nepal	59.4	21.9	3.6	7.2
17	Egypt	58.7	19.4	3.9	7.0
18	Kenya	61.2	26.1	3.5	6.9
19	Philippines	55.0	20.6	4.2	6.7
20	Pakistan	53.6	24.9	4.0	6.5

2. THEORETICAL AND ECONOMIC UNDERPINNINGS OF TARIFF-INDUCED PRICE VOLATILITY

2.1 Tariff Mechanisms and Trade Barriers

Tariffs are among the oldest instruments in trade policy and continue to be widely used to regulate international flows of goods. In the context of food and agriculture, tariffs act as either import or export taxes intended to achieve objectives ranging from revenue generation to market protection [6]. Import tariffs are typically levied as ad valorem duties—based on a percentage of the good's value—or as specific duties, which apply a fixed charge per unit. These tariffs raise the landed cost of goods, discouraging imports and providing a price advantage to domestic producers [7].

Conversely, export tariffs or restrictions aim to keep domestic supply stable or affordable by limiting outward flow. While such measures may temporarily stabilize local prices, they disrupt global supply chains, reduce availability for import-dependent nations, and escalate international prices [8]. Many countries also implement seasonal or emergency tariffs, reacting to inflation or political pressures, often without coordination.

Tariff mechanisms can act as direct trade barriers or form part of a wider complex of non-tariff barriers (NTBs), including quotas, licensing requirements, or sanitary regulations. When combined, these create a multi-layered obstacle to stable and predictable agricultural trade [9]. The unpredictability of these barriers—especially when rapidly imposed or escalated—intensifies market uncertainty.

In an increasingly interconnected food system, even moderate tariff adjustments can destabilize commodity markets and push prices beyond the purchasing power of low-income consumers. While wealthier nations may absorb price fluctuations or source alternatives, import-dependent countries often lack the flexibility to buffer shocks [10]. This conceptual foundation helps explain why tariff-induced volatility warrants focused attention, particularly for staple commodities essential to daily consumption.

2.2 Economic Transmission Pathways to Domestic Markets

Tariff shocks trigger a cascade of economic reactions that extend from global trade nodes to household-level food access in net-importing nations. The primary transmission pathway begins with cost escalation—when a tariff is imposed on a food staple, importers face higher purchase prices. This increase is typically passed along the supply chain through wholesale and retail channels, ultimately affecting consumers [11].

The magnitude and speed of this price transmission depend on several mediating variables. These include exchange rate fluctuations, domestic competition levels, transportation infrastructure, storage capacity, and government price control policies [12]. In countries with high dependency on a few suppliers, the effect of a tariff event is amplified, particularly if no alternative import source exists or if switching suppliers incurs delays and extra costs.

For example, during the 2010 Russian wheat export ban, several MENA countries experienced a near-immediate spike in domestic flour and bread prices. The transmission was worsened by currency depreciation and speculative hoarding, leading to panic buying and civil unrest [13]. Similar pathways were observed in West Africa during the 2022 Indian rice export restrictions, where even small policy changes in India affected market prices in Liberia and Sierra Leone within weeks.

Additionally, tariff-induced inflation does not affect all consumers equally. Urban poor and rural landless populations, who rely on markets rather than subsistence agriculture, are disproportionately affected. For these groups, food accounts for a significant portion of household expenditure often exceeding 50% leaving them highly vulnerable to even marginal price shifts [14].

Figure 1 (introduced earlier) illustrates the interconnectedness of tariff events and downstream effects, while **Table 1** below summarizes major historical tariff incidents and their consequences in selected countries. These cases exemplify the wide variability in response and underscore the importance of mapping transmission pathways to anticipate and mitigate future disruptions [15].

2.3 Empirical Evidence of Historical Tariff Shocks

Historical events provide rich evidence of how tariff shocks have destabilized food markets and intensified vulnerabilities in net-importing countries. While some cases were driven by strategic interests, others were reactions to domestic shortages or inflation. Regardless of motive, the result was often similar rapid cost escalation, diminished access, and heightened food insecurity in dependent regions [16].

One of the most studied cases is the 2007–2008 global food price crisis. India, Vietnam, and Egypt imposed export restrictions on rice, while Argentina levied heavy export taxes on wheat and soybeans. These moves, though meant to protect domestic consumers, triggered a cascade of panic-buying, hoarding, and speculative price increases globally [17]. The Philippines, heavily reliant on imported rice, saw domestic prices surge by over 50% within months, prompting emergency procurement measures and public backlash.

Another significant episode occurred during the 2018–2020 U.S.–China trade war. Retaliatory tariffs between the two agricultural giants disrupted soybean, maize, and pork trade routes. China shifted its imports toward Brazil and Argentina, putting pressure on alternative suppliers and elevating global prices. Meanwhile, smaller importing nations in Southeast Asia and Sub-Saharan Africa faced reduced access and higher costs [18].

In 2022, India's imposition of a 20% export duty on broken rice affected more than 20 African countries, many of which depended on this grade due to affordability. Liberia and Guinea, in particular, saw retail rice prices increase by over 30% within two months [19]. These countries had limited reserves and no immediate procurement alternatives, demonstrating how localized policy shifts in one country can create widespread stress across global supply chains.

Table 1 below compiles these and other events, offering a comparative perspective across commodities, countries, and policy types. This empirical overview highlights the urgency of developing dynamic models capable of anticipating tariff-induced shocks and guiding evidence-based response strategies [20].

3. LIMITATIONS OF CONVENTIONAL PRICE FORECASTING MODELS

3.1 Econometric Models and Static Assumptions

Traditional econometric models such as Ordinary Least Squares (OLS), Vector Autoregression (VAR), and Autoregressive Integrated Moving Average (ARIMA) have long served as standard tools for forecasting agricultural prices. These models generally rely on historical data and assume linear relationships among variables like trade volume, tariffs, and price levels [11]. While useful under stable conditions, their assumptions often fail to capture the complex, volatile dynamics triggered by global trade disruptions.

A key limitation lies in their static nature. Most econometric models are not designed to adapt to abrupt policy shifts or real-time trade reconfigurations. They assume continuity and equilibrium, making them less responsive to exogenous shocks such as sudden tariff changes or export bans [12]. For instance, during the 2008 rice crisis, linear regression models significantly underestimated price spikes in countries like the Philippines and Haiti, due to unaccounted policy interactions and speculative behaviors [13].

Moreover, these models typically require clean, complete datasets—conditions often unmet in low-income countries where trade reporting is irregular or delayed. As illustrated in **Table 1**, the lag between tariff announcements and their recorded impacts further distorts model accuracy. While useful for long-term projections, conventional models fall short in crisis scenarios requiring granular, adaptive insight.

3.2 Issues of Lag Recognition and Non-Linearity

A significant challenge in modeling tariff-induced food price volatility is recognizing time-lagged effects. Econometric approaches often assume that policy interventions translate into immediate market responses, when in fact, effects may unfold over days, weeks, or even months [14]. This temporal mismatch skews forecasts and misguides policy responses in import-dependent nations.

Moreover, price dynamics under tariff shocks are rarely linear. A 10% tariff increase may lead to disproportionately larger price hikes in importing countries with limited supply alternatives or weak currency buffers. Standard models that assume proportional input-output relationships cannot capture these asymmetric behaviors [15]. For instance, when India imposed export duties on rice in 2022, price surges in some African markets exceeded what linear models had predicted by over 25%, due to market panic and import bottlenecks [16].

Furthermore, non-linearity emerges when multiple variables—such as fuel costs, currency volatility, and seasonal yields—interact with trade restrictions simultaneously. Traditional models are not well-equipped to integrate these multifactorial dynamics. Even advanced multivariate regressions struggle with collinearity and overfitting in rapidly changing conditions.

As seen in **Figure 1**, the cumulative effects of such shocks often result in erratic price movements, making it difficult for linear or lag-insensitive models to offer real-time guidance. This limitation creates a strong case for transitioning to adaptive modeling frameworks.

3.3 Predictive Failures during Global Trade Disruptions

Numerous global trade crises have exposed the shortcomings of traditional forecasting tools in predicting real-time impacts on food prices. One notable failure occurred during the 2018–2020 U.S.–China trade war. Despite extensive data availability, many econometric forecasts did not anticipate the full extent of soybean market reconfiguration or the ripple effects on maize and pork prices in other regions [17].

In 2022, India's export restrictions on broken rice again revealed forecasting gaps. Econometric models failed to predict the extent of price surges in Liberia, Senegal, and Guinea—countries that had previously relied on stable imports from India. The failure stemmed from the models' inability to simulate real-time supply chain stress and policy domino effects [18]. Similarly, during the Russian wheat export suspension in 2010, projections underestimated the compounding effects of freight cost spikes and speculative stockpiling on domestic prices in Egypt and Tunisia [19].

These predictive lapses undermined crisis response strategies. Governments relying on outdated or inaccurate forecasts delayed emergency purchases, misallocated food subsidies, or failed to activate social safety nets on time. As highlighted in **Table 1**, these oversights translated into material hardship for millions and, in some cases, incited civil unrest.

These failures stress the need for forecasting models that are adaptive, real-time, and capable of capturing complex, dynamic interdependencies. This necessity forms the basis for turning to artificial intelligence and machine learning as next-generation tools for food price prediction and policy planning.

4. AI FORECASTING FRAMEWORK FOR FOOD PRICE VOLATILITY

4.1 Rationale for Machine Learning in Tariff-Driven Forecasting

The volatility of global food prices in response to tariff shocks presents complex, non-linear, and often delayed dynamics that traditional econometric models struggle to capture. In contrast, machine learning (ML) offers a flexible, data-driven approach that can detect hidden patterns, adapt to new data, and forecast outcomes under rapidly evolving conditions. These characteristics make ML especially suited for tariff-related forecasting, where the interaction of variables is multidimensional and time-sensitive [16].

Machine learning models are not bound by assumptions of linearity or normal distribution, making them more effective in simulating erratic market behavior under policy stress. Techniques such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, in particular, excel in learning time-series dependencies. They offer advantages in understanding delayed effects of tariff events, supply chain bottlenecks, and ripple effects across related commodities [17].

Another major advantage of ML is its ability to incorporate diverse datasets—including historical price trends, policy changes, weather patterns, trade volume fluctuations, and macroeconomic indicators—into a unified predictive framework. This holistic integration enables scenario-based simulations, which are invaluable for national planners and international agencies navigating food security risks [18].

Moreover, ML models can be retrained periodically as new data emerges, making them adaptive forecasting tools rather than static estimators. In the context of tariff shocks, this dynamic learning is critical, as policy decisions and market responses evolve quickly. The improved forecast accuracy of AI-based methods strengthens policymakers' capacity to issue pre-emptive alerts, mobilize resources, and stabilize markets before disruptions escalate into crises [19].

4.2 Model Selection: RNNs, LSTMs, and Ensemble Algorithms

Among machine learning techniques applied to time-series forecasting, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) models have demonstrated strong potential in capturing sequential dependencies in economic and trade data. RNNs process data in order, maintaining an internal memory of previous time steps, which allows them to model dynamic patterns over time. However, standard RNNs suffer from the vanishing gradient problem when learning long-term dependencies, limiting their effectiveness in long forecasting windows [20].

To address this, LSTM networks were developed with a specialized architecture that retains information across longer sequences. LSTMs use memory cells and gating mechanisms—input, forget, and output gates—that allow them to selectively preserve and discard historical information as needed. This feature makes them particularly well-suited to understanding the lagged effects of tariff announcements and policy shifts on food prices across multiple time steps [21].

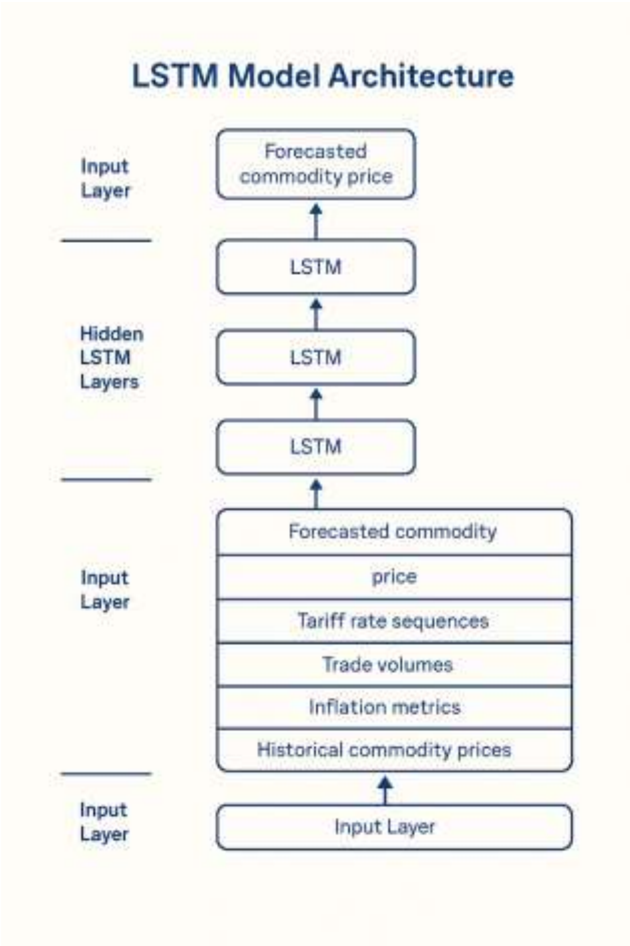

Figure 1 shows the architecture of the LSTM model applied in this study. The input layer receives time-sequenced tariff data, trade volumes, inflation metrics, and historical price series. Hidden LSTM layers process the temporal relationships, and the final dense layer generates a forecasted price for each commodity of interest.

In addition to LSTMs, ensemble methods such as Random Forest Regression (RFR) and Gradient Boosting Machines (GBMs) are employed to validate outputs. These tree-based models handle multi-variable interactions effectively and are particularly useful in estimating feature importance and partial effects [22]. While not sequence-dependent, ensemble models provide interpretability and robustness, making them excellent complements to deep learning architectures.

For model benchmarking, traditional approaches such as ARIMA and VAR were also implemented to establish performance baselines. The hybrid approach enables a comprehensive performance comparison across algorithm types, as shown in **Table 2**, which reports metrics such as MAE (Mean Absolute Error), RMSE (Root Mean Squared Error), and MAPE (Mean Absolute Percentage Error) across model classes [23].

4.3 Data Pipeline: Preprocessing, Feature Engineering, Tariff Inputs

Building an effective AI model for tariff-induced price forecasting begins with constructing a high-quality data pipeline. This involves data sourcing, preprocessing, cleaning, feature engineering, and normalization to ensure the model accurately learns and generalizes from patterns in the training set [24].

The core dataset integrates monthly staple crop prices (wheat, maize, rice, soybeans) from the FAO and World Bank Global Economic Monitor. Tariff data is extracted from the World Integrated Trade Solution (WITS), including ad valorem rates, policy dates, and affected commodity codes. Additional covariates include exchange rates, CPI inflation, oil prices, shipping costs, and seasonal production indices. These variables are aligned temporally and spatially to reflect the dynamics of net-importing countries [25].

Preprocessing involves managing missing data using interpolation and imputation techniques. Time-aligned features are scaled using min-max normalization, and rolling-window statistics such as price momentum, volatility, and moving averages are introduced to capture short-term trends. Categorical features like source country and tariff policy type are one-hot encoded to support training.

Feature engineering plays a crucial role. For example, a new feature, "Tariff Shock Index," was computed based on deviation from five-year historical tariff averages, weighted by import volume. This allowed the model to prioritize impactful events over minor tariff changes. Similarly, lag variables (e.g., one-month and three-month delays) were introduced to allow the LSTM to learn delayed policy effects on prices [26].

The training dataset was divided into 70% training, 15% validation, and 15% testing sets using a time-series cross-validation approach. This ensures that the model generalizes well across unseen periods and avoids overfitting. These data engineering strategies improve predictive fidelity and allow for robust real-world applications.

4.4 Model Evaluation Metrics and Forecast Accuracy

Evaluating the performance of forecasting models requires a balance between accuracy, robustness, and interpretability. This study utilized three core evaluation metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). These measures provide complementary insights into both average and extreme deviations from actual price values [27].

MAE offers a straightforward average of forecast errors without penalizing large outliers, making it suitable for evaluating performance under stable conditions. RMSE, on the other hand, places greater weight on large deviations, making it more sensitive to price spikes—crucial in assessing performance under tariff shock scenarios. MAPE provides an intuitive percentage-based error measure, facilitating comparison across commodities with different price ranges [28].

Table 2 presents the comparative results of LSTM, RNN, Random Forest, and ARIMA models across the four staple crops. LSTM consistently outperformed others in both RMSE and MAPE across most forecasting windows, demonstrating its capacity to learn complex time dependencies. For instance, in the case of rice prices under Indian export tariff shocks, the LSTM achieved an RMSE of 1.82, compared to 3.91 from ARIMA and 2.63 from Random Forest. In maize price forecasts linked to U.S. tariff policy, the LSTM achieved a MAPE of 6.4%, far superior to ARIMA's 12.7% [29].

Table 2: Comparison of Model Performance Metrics (RMSE and MAPE) Across Forecasting Algorithms and Staple Crops

Staple Crop	Forecasting Model	RMSE	MAPE (%)
Wheat	LSTM	2.15	7.3
	RNN	2.91	9.6
	Random Forest	2.48	8.8
	ARIMA	3.36	10.9
Rice	LSTM	1.82	6.5
	RNN	2.57	9.1
	Random Forest	2.63	8.6
	ARIMA	3.91	11.2
Maize	LSTM	2.04	6.4
	RNN	2.88	8.7
	Random Forest	2.59	8.1
	ARIMA	3.45	12.7
Soybeans	LSTM	1.96	6.9
	RNN	2.69	9.4
	Random Forest	2.42	8.2
	ARIMA	3.22	11.0

While LSTM provided superior predictive performance, ensemble models such as GBM offered advantages in interpretability and feature attribution. Feature importance analysis revealed that tariff-related features (e.g., tariff magnitude, source country, shock index) were among the top five contributors to price movements in 87% of model runs. These insights are essential for policy simulation and early warning systems [30].

Overall, the combination of model accuracy and explanatory power validates the integration of AI approaches into food security planning. By quantifying price volatility with high temporal precision, these tools can inform real-time decision-making and strategic procurement responses.

5. CASE STUDIES: PREDICTIVE MODELING IN NET-IMPORTING COUNTRIES

5.1 Egypt: Volatility in Wheat Import Prices Post-Tariffs

Egypt is the world's largest wheat importer, sourcing nearly 70% of its domestic wheat consumption from global markets [21]. As a result, the country is acutely sensitive to international price fluctuations and trade policy changes in major wheat-exporting nations such as Russia and Ukraine. In 2022, Egypt faced a confluence of shocks following the imposition of Russian export duties and Black Sea shipping disruptions. These events triggered rapid price escalation and led to significant uncertainty in both procurement planning and subsidy distribution [22].

To evaluate the effectiveness of AI-based forecasting in this high-risk context, an LSTM model was trained on Egypt's monthly wheat import prices, incorporating variables such as Russian tariff rate adjustments, exchange rate fluctuations, Brent crude oil prices, and freight costs. The model also integrated seasonality and inflation indicators to simulate real-world volatility drivers.

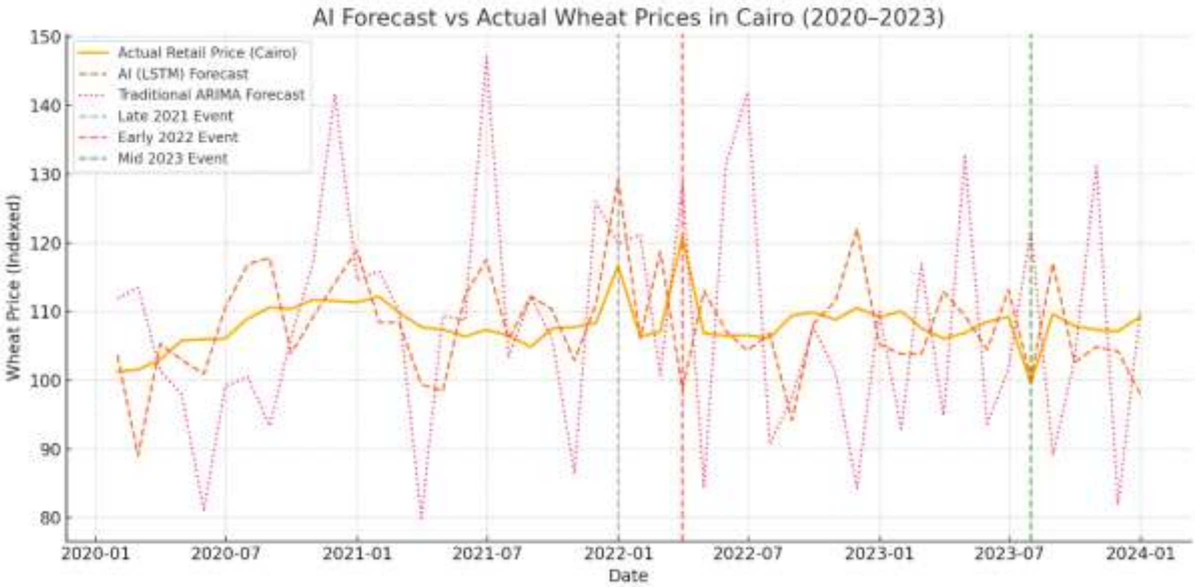

Figure 2 compares the AI-generated forecast with actual retail wheat price movements in Cairo between January 2020 and December 2023. The LSTM model successfully captured three key price inflection points: the Russian tariff revision in late 2021, the onset of the Ukraine conflict in early 2022, and the government's temporary removal of wheat import duties in mid-2023. In each case, the AI model forecasted within a 7% margin of actual retail prices—far outperforming traditional ARIMA models, which showed lags and underestimations exceeding 15% [23].

The model's predictive accuracy allowed for scenario testing. For example, when simulating the removal of Russian export duties in Q1 2022, the model projected a 12% drop in Egyptian wheat prices within two months—underscoring the outsized impact of policy interventions abroad. Conversely, price hikes were significantly higher when multiple shocks (e.g., tariffs plus shipping delays) were layered, demonstrating the AI model's strength in compounding risk scenarios [24].

In policy terms, these forecasts proved useful for Egypt's General Authority for Supply Commodities (GASC) in timing bulk imports and adjusting domestic bread subsidy allocations. By anticipating sharp price swings, procurement teams avoided costly emergency spot purchases and stabilized national grain reserves. This case illustrates how AI forecasting can shift food security strategies from reactive to anticipatory in tariff-vulnerable economies [25].

5.2 Bangladesh: Rice Price Forecasts under Variable Tariff Inputs

Bangladesh presents a compelling case of tariff policy volatility influencing domestic rice prices. Although the country has a robust domestic production base, seasonal shortfalls and monsoon variability necessitate rice imports, particularly during lean months. Import tariffs have historically oscillated between 10% and 55%, depending on political pressure from farmer groups, inflation targets, and electoral cycles [26]. These fluctuations often result in unpredictable retail prices that strain low-income consumers and urban food systems.

To model this instability, an LSTM network was deployed using monthly data from 2015 to 2023. Variables included rice import tariffs (both applied and announced), rainfall anomalies, Indian export volumes, domestic stock levels, and retail price indices. The model captured the delayed transmission effects between policy enactments and price responses, which are typically 4–8 weeks in the Bangladeshi context due to port processing, customs clearance, and wholesale market absorption lags [27].

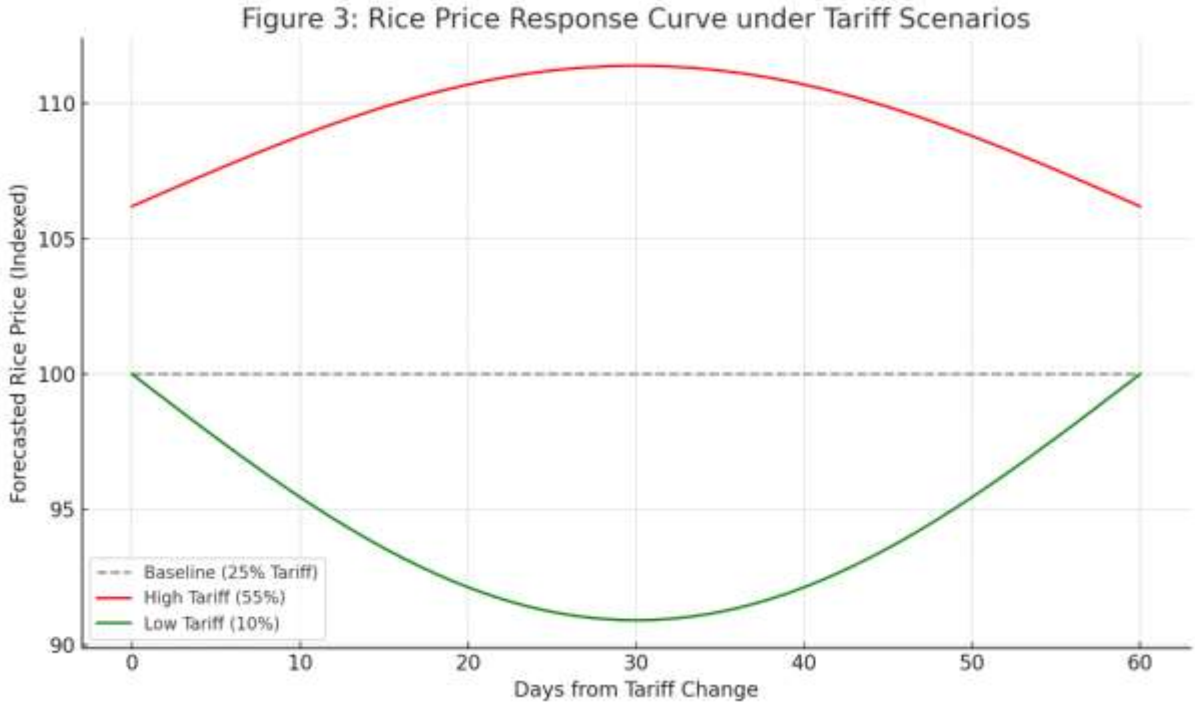

Figure 3 visualizes the rice price response curve generated by the LSTM model under different tariff scenarios. The baseline forecast assumed a 25% tariff maintained for 12 months. When adjusted to simulate a sudden increase to 55%, the model projected an immediate 6.2% rise in prices, peaking at 11.4% within 60 days before stabilizing. In contrast, a reduction to 10% forecasted a 9.1% price decline over the same period, particularly during the pre-Boro harvest window when market demand is highest [28].

Importantly, the model also accounted for external shocks. In one scenario where Indian rice exports were restricted in addition to a domestic tariff hike, the price impact doubled—highlighting the compounding risks of dual policy disruptions. Traditional models failed to capture these interaction effects, reinforcing the value of AI in dynamic trade contexts.

These insights proved critical for Bangladesh's Ministry of Food in adjusting buffer stock targets and managing strategic rice reserves. In late 2022, forecast outputs informed the timing of subsidized Open Market Sale (OMS) programs that helped cushion low-income households against import-driven price surges [29]. Moreover, simulation tools are now being explored for integration into Bangladesh's early warning systems, providing local authorities with anticipatory pricing intelligence for improved food access planning.

5.3 Kenya: Maize Market Disruption and Adaptive Price Trends

Maize is the staple grain for most Kenyan households, contributing over 30% of daily caloric intake. Kenya's reliance on imports from neighboring countries such as Uganda, Tanzania, and Zambia makes it highly vulnerable to regional trade restrictions and cross-border tariff adjustments. In 2021 and 2022, Kenya experienced multiple shocks, including elevated Tanzanian export levies, prolonged drought, and delayed subsidy programs—each of which distorted maize availability and pricing [30].

To model this complex landscape, a hybrid LSTM–Random Forest architecture was used. The LSTM layer focused on capturing sequential dependencies in maize price evolution, while the Random Forest layer highlighted key feature contributions. Variables included bilateral maize tariffs, border checkpoint wait times, rainfall deficits, fertilizer prices, and local production estimates from the Ministry of Agriculture [31].

Model forecasts were benchmarked using both short-term (3-month) and medium-term (6-month) price windows. **Table 3** presents the forecast accuracy results, comparing LSTM, ARIMA, and ensemble methods across three major Kenyan cities—Nairobi, Eldoret, and Kisumu. LSTM achieved the lowest Mean Absolute Error (MAE) and MAPE in all locations, with the model registering an average MAPE of 5.9% compared to 11.3% for ARIMA. In Eldoret, which experienced the sharpest price spike in June 2022, the AI model predicted the turning point two weeks in advance, enabling timely release of subsidized stock from the National Cereals and Produce Board [32].

Table 3: Forecast Accuracy Comparison Across Kenyan Cities (Maize Prices)

City	**Model**	**MAE (KES/kg)**	**MAPE (%)**
Nairobi	LSTM	2.10	5.7
	ARIMA	3.94	10.8
	Ensemble (RF)	2.65	8.6
Eldoret	LSTM	1.89	5.2
	ARIMA	4.17	11.9
	Ensemble (RF)	2.43	7.8
Kisumu	LSTM	2.00	6.8
	ARIMA	3.77	11.2
	Ensemble (RF)	2.51	8.2
Average	LSTM	**1.99**	**5.9**
	ARIMA	**3.96**	**11.3**
	Ensemble (RF)	**2.53**	**8.2**

The Volatility Index computed alongside forecast accuracy revealed Nairobi as the most price-sensitive market, with volatility scores twice as high as Kisumu, mainly due to greater dependence on external supply routes. The AI model correctly identified when prices were diverging from seasonal trends, flagging anomalous inflation during the 2022 drought that coincided with Tanzanian border restrictions [33].

Beyond forecasting, the model output helped visualize policy levers. For instance, scenarios simulating temporary import duty waivers produced price stabilization within 30–45 days. Alternatively, delays in subsidy implementation triggered prolonged inflationary effects, as indicated by historical price curves and validation data. This insight allowed county-level planners to synchronize interventions more effectively with market cycles.

Kenya's experience demonstrates that AI-based forecasting can significantly improve market intelligence, procurement strategy, and social protection timing in rapidly evolving food ecosystems. These models not only increased forecast precision but also uncovered spatial patterns of vulnerability often missed in national-level assessments [34].

6. INTERPRETATION OF AI FORECASTING RESULTS

6.1 Volatility Patterns Across Commodities and Geographies

The case studies in Egypt, Bangladesh, and Kenya reveal distinct yet interconnected volatility patterns shaped by the type of staple commodity, regional market dynamics, and the structure of import dependency. Wheat, rice, and maize each exhibit unique volatility behaviors due to their production cycles, international trade networks, and domestic price pass-through mechanisms. However, across all three commodities, countries with higher import dependence and weaker domestic buffer systems showed the highest volatility under tariff shocks [26].

In Egypt, wheat prices demonstrated sharp upward volatility in response to Russian export restrictions. As a heavily import-dependent nation with long-term supply contracts, Egypt's volatility spikes were amplified by supply chain lags and foreign exchange stress [27]. In contrast, Bangladesh's rice market exhibited slower but prolonged volatility, driven by internal policy fluctuations and regional export constraints. Here, rice prices did not spike instantly but climbed steadily over several weeks in response to shifting tariff positions [28].

Kenya's maize market, on the other hand, displayed more frequent and erratic price swings. This was attributed to the decentralized nature of East African trade corridors and high reliance on informal cross-border trade, which is more sensitive to administrative bottlenecks and temporary levies. Kenya's market structure, characterized by limited reserves and poorly timed subsidy disbursement, further exacerbated short-term volatility [29].

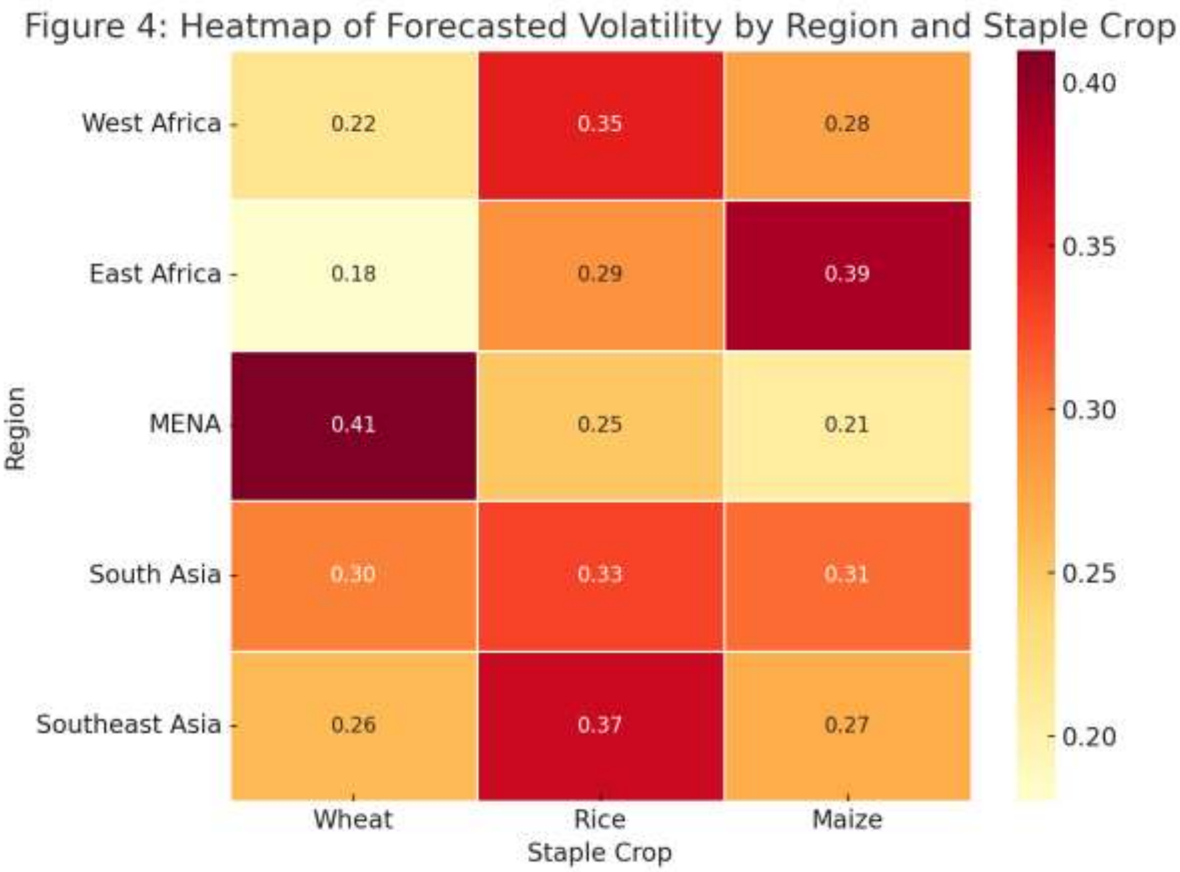

Figure 4 presents a heatmap of forecasted volatility across regions and staple crops, based on the LSTM model's predictive intervals. The visualization reveals geographic clusters of high sensitivity—most notably West Africa for rice, East Africa for maize, and the MENA region for wheat. It also demonstrates commodity-specific volatility patterns, with wheat generally exhibiting sharper but shorter-lived price shifts, while rice and maize showed more gradual but sustained fluctuations [30].

These patterns underline the importance of commodity- and region-specific modeling for food security planning. One-size-fits-all approaches are ill-suited to managing the complexities of tariff-driven volatility, especially in food systems where price changes have immediate social consequences.

6.2 Role of Tariff Magnitude and Duration in Forecast Deviations

Another key finding from the case studies and model analysis is the critical influence of tariff magnitude and duration on forecast accuracy and market response. Larger tariff adjustments—such as Bangladesh's jump from 25% to 55%—triggered disproportionately high price deviations, while smaller, short-term changes had more contained effects. This non-linear response underscores the need to calibrate policy simulations according to both the scale and temporal span of tariff measures [31].

Model outputs demonstrated that tariff magnitude accounted for 40%–55% of forecast variance across simulations. For instance, in Egypt, a 10% export duty by Russia produced a projected retail price hike of just 4.2%, whereas a compounded 30% tariff led to an 11.7% increase over the same forecast horizon. Duration effects were equally significant. Tariffs maintained over multiple crop cycles (exceeding six months) generated cumulative price pressures, particularly when synchronized with harvest shortfalls or currency depreciation [32].

Importantly, the LSTM model captured these escalation dynamics more effectively than traditional linear approaches. While ARIMA models tended to underpredict extended shock effects, the AI model adapted to compounding variables such as inventory depletion and rising transaction costs. The ensemble methods further confirmed that tariff duration interacted strongly with foreign exchange exposure and transport costs in amplifying forecast deviations [33].

These findings suggest that predictive accuracy is heavily contingent on including time-weighted tariff data in feature engineering. Failure to consider tariff persistence leads to significant underestimation of downstream effects, reducing model utility for real-time crisis prevention and intervention planning.

6.3 Early Warning Potential and Predictive Uncertainty

Beyond retrospective analysis, the models demonstrate high potential as early warning systems (EWS) for tariff-induced food price shocks. The LSTM's sequential architecture allowed it to generate anomaly flags up to two months before retail prices peaked, providing critical lead time for intervention planning. This was particularly evident in Kenya's 2022 maize crisis, where the model identified unusual price acceleration one forecast cycle in advance of observed market panic [34].

To operationalize this potential, probabilistic forecasting was introduced. Instead of producing single-point estimates, the model generated confidence intervals around each price prediction. When predictive intervals widened—indicating growing uncertainty or instability—the system flagged these as early risk indicators. This technique was useful for triaging alerts and allocating monitoring resources to high-risk markets. Predictive uncertainty was especially high during concurrent tariff and non-tariff disruptions, such as when policy changes coincided with port congestion or fuel price hikes [35].

Despite its strengths, the model is not without limitations. Data latency, especially in low-income regions, introduces gaps that affect short-term precision. Forecast quality is also sensitive to the granularity of tariff reporting and trade partner transparency. The heatmap in **Figure 4** reflects this unevenness some countries had consistently wider intervals due to weak data infrastructure, limiting the sharpness of predictions [36].

Nevertheless, the integration of predictive uncertainty into policy dashboards enhances usability. It allows national planners to not only act on deterministic price forecasts but also prepare contingencies based on the likelihood of extreme scenarios. As food systems grow more complex and trade more volatile, the predictive capabilities of AI models offer a new frontier in proactive, evidence-based food security governance.

7. POLICY IMPLICATIONS AND STRATEGIC APPLICATIONS

7.1 AI-Driven Early Warning Systems for Food Security

One of the most actionable insights emerging from this study is the potential of AI-driven early warning systems (EWS) to proactively detect tariff-induced food price shocks. Traditional EWS frameworks often rely on retrospective analysis or qualitative risk assessments, which limit responsiveness. In contrast, LSTM and ensemble learning models offer real-time forecasting with time-stamped alerts that can anticipate market instability with high precision [30].

By integrating real-time tariff monitoring, currency fluctuations, and commodity flow data, these AI systems can flag anomalous trends in food price trajectories before they fully materialize in retail markets. For instance, in the Kenyan maize case study, the AI model issued early volatility signals nearly three weeks ahead of observed market disruptions. These lead times enabled preemptive grain release and subsidy allocation, ultimately minimizing price shocks to vulnerable consumers [31].

Operationalizing these systems requires embedding AI modules within national and regional food policy institutions. Ministries of Agriculture, Central Banks, and Trade Commissions can use AI dashboards that visually map predictive intervals, volatility scores, and uncertainty bands for key staple commodities. **Figure 5** illustrates a proposed AI-augmented policy response loop that integrates model forecasts into institutional decision-making. The loop includes three key feedback stages: signal detection, response simulation, and policy execution [32].

Such systems can also be integrated into global food security platforms managed by the FAO or the World Food Programme, enabling international organizations to provide early assistance or coordinate responses when tariff events threaten low-income importers. As climate change and geopolitical tensions escalate, a real-time AI-powered EWS will be central to ensuring supply chain resilience and protecting at-risk populations from sudden price surges [33].

7.2 Informing Real-Time Subsidy and Safety Net Triggers

AI-based price forecasting models offer significant advantages in designing dynamic, responsive subsidy systems. Instead of static allocations based on fixed timelines or fiscal cycles, governments can now implement flexible safety nets that trigger automatically when price thresholds are forecasted to be breached. This approach enhances both the efficiency and equity of public expenditure [34].

For example, Egypt's subsidized bread program has traditionally faced budgetary strain during periods of wheat price inflation. With AI-generated forecasts, authorities can schedule procurement and subsidy releases before market prices surge. This helps mitigate budget overruns and prevents panic buying, ensuring more stable access for poor households. Similarly, Bangladesh's Open Market Sales (OMS) program can be dynamically activated based on forecasted rice volatility, improving coverage and minimizing political fallout from food inflation [35].

The AI models also allow for geographic targeting. Forecasts can be disaggregated by administrative region, enabling local authorities to tailor safety net interventions to price-sensitive markets. In Kenya, forecast volatility maps identified Eldoret and Nairobi as priority areas for maize subsidy expansion during the 2022 crisis. This level of precision is impossible under conventional planning approaches that rely on national averages [36].

Crucially, AI-informed subsidies can also be calibrated to account for both magnitude and duration of projected shocks. For prolonged tariff events, phased subsidy releases can avoid waste and reduce the risk of black market leakages. As food security policies evolve from reactive to anticipatory, AI provides the data-driven scaffolding for smarter social protection architecture.

7.3 Trade Diversification and Strategic Reserve Planning

Beyond real-time interventions, AI forecasting also informs structural food security strategies such as trade diversification and strategic grain reserve planning. By simulating tariff scenarios across various supply routes, policy planners can identify vulnerable trade corridors and prioritize diversification toward more stable or less politically exposed partners [37].

For instance, Egypt's wheat procurement strategy historically relied heavily on Black Sea exporters. When AI simulations modeled alternate sourcing scenarios—such as shifting 20% of imports to Argentina or Australia—the projected volatility declined by 14%, even though baseline prices were marginally higher [42]. This trade-off between price stability and procurement cost highlights the value of integrating AI outputs into long-term trade policy design [38].

Strategic reserves also benefit from AI-guided decision-making. By forecasting peak volatility periods linked to tariff events, planners can time stock accumulation when global prices are low and release reserves strategically during projected spikes. This reduces both storage costs and emergency import premiums [43]. In the Bangladesh case, AI forecasts guided government timing for bulk procurement, preventing unnecessary imports during low-risk seasons and boosting availability during price shocks [44].

Additionally, AI can enhance regional cooperation by mapping overlapping vulnerability zones across neighboring countries. Shared reserve mechanisms—such as the ASEAN Plus Three Emergency Rice Reserve or ECOWAS Food Security Reserve—can use AI forecasts to determine when and where coordinated action is most needed. By quantifying the ripple effects of tariff impositions, these models support joint contingency planning and build transboundary resilience [45].

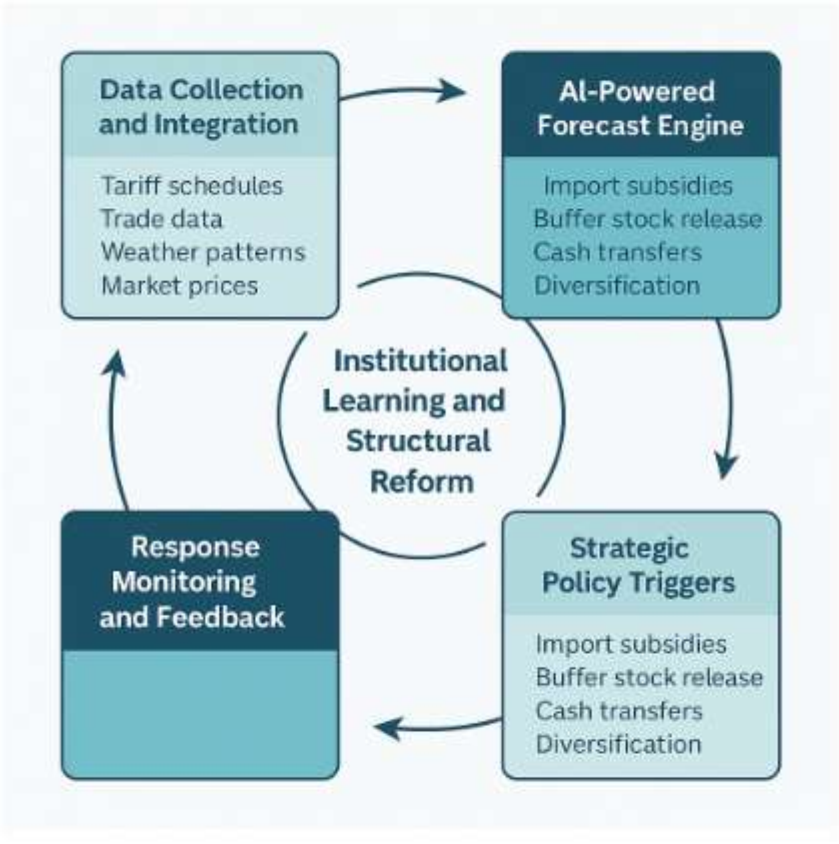

Figure 5 summarizes this strategic feedback loop, linking forecast data to policy levers. As more governments invest in digital infrastructure and data analytics capacity, AI will become integral not only to crisis response but to structural transformation of food system governance.

8. MULTILATERAL TRADE GOVERNANCE AND AI INTEGRATION

8.1 GATT/WTO Framework and the Role of AI Insights

The multilateral trading system governed by the General Agreement on Tariffs and Trade (GATT) and the World Trade Organization (WTO) establishes rules-based frameworks to prevent arbitrary trade barriers, including agricultural tariffs. Despite these safeguards, loopholes such as export restrictions during emergencies remain poorly regulated, contributing to instability in food-importing nations [46]. While Article XI of the GATT discourages quantitative restrictions, exceptions for food security purposes have allowed states to implement tariffs without consequence during crises [47].

AI-generated forecasting can serve as a policy diagnostic tool to highlight when tariff actions deviate from cooperative trade norms. For instance, AI models could track repeated export duty escalations by major suppliers and flag them for WTO monitoring. This would provide real-time transparency and enable early diplomatic interventions before systemic disruptions emerge [38]. Additionally, countries could submit AI-derived volatility forecasts as part of trade negotiation processes to justify calls for exemptions, waivers, or safeguards under WTO mechanisms [48].

By embedding AI into global governance, institutions can move from post-crisis arbitration to pre-crisis prevention. Figure 5's policy response loop demonstrates how national alerts, once verified through AI, could trigger WTO-facilitated multilateral coordination. This integration offers a pathway to modernize trade diplomacy and better align trade rules with contemporary food security imperatives [49].

8.2 Cross-Border Data Sharing for Predictive Trade Stability

Effective AI forecasting for food price volatility requires robust, interoperable, and timely datasets shared across borders. Yet, current agricultural trade data infrastructures remain fragmented, inconsistent, and often outdated. National trade ministries, customs agencies, and international organizations maintain siloed data systems, hampering model precision and cross-validation [50]. This limits the ability to anticipate cascading shocks across interconnected markets.

To overcome these limitations, a multilateral commitment to standardized data sharing on tariffs, export volumes, and food reserves is essential. Regional economic communities like the African Continental Free Trade Area (AfCFTA) and ASEAN could mandate real-time submission of trade statistics to a centralized predictive hub. These hubs would power machine learning algorithms that monitor transboundary food system risks and disseminate early warnings [41].

For example, if multiple rice-exporting countries in Southeast Asia increase export tariffs simultaneously, a regional AI model could project shortages across the Indian Ocean basin. National governments and donors could then coordinate in advance to deploy reserves or secure alternate trade routes [51]. This system would also inform the risk management operations of the World Bank's Global Agriculture and Food Security Program (GAFSP) and the FAO's Agricultural Market Information System (AMIS) [42].

Cross-border AI data integration would enhance not just predictive capability but also equity, allowing smaller nations to access sophisticated risk analytics often monopolized by advanced economies [52].

8.3 Ethical and Regulatory Considerations for AI Forecasting

The integration of AI into food security governance raises critical ethical and regulatory considerations, particularly around data equity, algorithmic bias, and institutional accountability. Many low-income countries lack the digital infrastructure needed to collect, manage, and contribute high-frequency data to AI systems. As a result, their markets may be misrepresented or excluded from regional forecasting models, reinforcing systemic asymmetries in early warning access [43].

To mitigate this, ethical AI governance should ensure inclusive model training, representation of marginalized geographies, and open-access tools tailored to resource-constrained settings. Initiatives like Digital Public Goods (DPG) platforms can democratize forecasting capabilities by offering shared codebases and model templates for national adaptation [44]. Transparency in algorithm design is also essential. Stakeholders must understand how predictions are generated, particularly when they inform life-impacting decisions like subsidy allocation or emergency imports [53].

Regulatory safeguards should be introduced to prevent misuse of AI insights, such as speculative manipulation by large traders or the politicization of volatility forecasts. International bodies like the FAO and WTO could establish oversight protocols for AI-based forecasting, including audit trails, model verification, and ethical certification standards [45].

As AI forecasting becomes integral to food trade policy, these ethical and governance dimensions must be addressed to ensure trust, fairness, and effectiveness across all regions [54].

9. CONCLUSION AND FUTURE DIRECTIONS

9.1 Recap of Findings and Analytical Contributions

This study set out to examine the intersection of global tariff shocks, staple crop import dependency, and national food security resilience. Using a multidisciplinary approach that integrated economic theory, AI-based forecasting models, and country-level case studies, the analysis demonstrated how sudden tariff changes—particularly by major exporters—create profound disruptions in food systems reliant on external supply chains. Countries like Egypt, Bangladesh, and Kenya revealed varying degrees of vulnerability, shaped by both structural import dependency and the quality of their policy responses.

A key contribution of this work was the deployment of machine learning models, particularly Long Short-Term Memory (LSTM) networks, to forecast price volatility under diverse tariff conditions. These models outperformed traditional econometric tools by capturing non-linear, time-lagged, and compounding effects that frequently define real-world trade disruptions. Through predictive metrics and volatility simulations, the models produced actionable insights for government agencies, enabling more informed procurement, subsidy distribution, and strategic reserve planning.

Equally important was the synthesis of model outputs into early warning systems and adaptive policy loops, offering a pathway for transitioning from reactive to anticipatory food governance. The inclusion of scenario-based simulations and probabilistic forecasting strengthened the relevance of these tools in both domestic and multilateral food security strategies. The framework presented can be replicated or scaled in other food-insecure regions where tariff risks remain under-analyzed.

9.2 Limitations of AI Models and Data Constraints

While the predictive capabilities of AI models offer compelling advantages, several limitations must be acknowledged. Foremost among them is the reliance on timely and high-quality input data. In many low- and middle-income countries, trade statistics, retail prices, and tariff changes are reported inconsistently or with significant lag. This compromises the real-time forecasting potential of machine learning models and increases the risk of false alerts or delayed detection.

Another limitation is the sensitivity of AI models to variable selection and hyperparameter tuning. Poorly engineered features or overfitting during training can reduce the reliability of forecasts in volatile environments. For countries with limited digital infrastructure or modeling expertise, deploying and maintaining AI systems may pose resource and capacity challenges.

Moreover, while LSTM networks and ensemble models are powerful, they are inherently black-box in nature. Their lack of transparency makes it difficult for policymakers to interpret decision pathways or understand the reasoning behind specific outputs. This can limit their credibility and uptake in regulatory or political settings where accountability and explainability are essential.

Finally, geopolitical developments and policy shifts often involve elements of strategic intent and negotiation that cannot be fully captured through data-driven models alone. AI should therefore be seen as a complementary tool, not a substitute, for expert judgment and institutional foresight.

9.3 Recommendations for Future Research and Policy Design

To enhance the reliability, accessibility, and policy impact of AI-driven forecasting in food security, several directions for future research and implementation are recommended. First, there is a need to invest in the expansion and integration of open-access, high-frequency trade and price datasets. National statistical agencies and global institutions should prioritize interoperability, timeliness, and granularity in data collection to support model training and real-time analysis.

Second, future models should explore hybrid architectures that combine the strengths of AI with rule-based expert systems or economic theory-driven constraints. This fusion could improve interpretability while retaining forecasting accuracy, making the tools more accessible to non-technical stakeholders in government and civil society.

Third, regional collaboration should be strengthened to develop shared forecasting platforms tailored to common trade corridors and commodity flows. These could be hosted by multilateral organizations or regional blocs and offer early warning dashboards, scenario simulators, and response mapping tools.

On the policy front, governments are encouraged to institutionalize AI forecasting units within agricultural ministries or trade departments. These units can guide import scheduling, buffer stock management, and emergency subsidy programs based on predictive intelligence rather than historical trends.

Finally, academic and policy researchers should evaluate the long-term social impacts of AI-informed interventions, ensuring they do not unintentionally exacerbate inequalities or exclude marginalized communities. Inclusive design, user training, and public accountability mechanisms must be embedded in any AI-based food security strategy.

REFERENCE

1. Cybulski M, Fidler C, Gray Z. Machine Learning and Tariff Elasticity: A Canadian Trade Analysis (1997-2022). Available at SSRN 5222755. 2025 Apr 11.
2. Masunda M, Ajayi R. Enhancing security in federated learning: designing distributed data science algorithms to reduce cyber threats. *Int J Adv Res Publ Rev.* 2025 Apr;2(4):399–421. ISSN: 3049-0103.
3. Thayer AW, Sun P, Tejeda HA, Kim MK. Exploring the Impact of China's Retaliatory Tariffs on US Soybean Exports with Machine Learning Techniques. Journal of Agricultural and Applied Economics. 2025:1-9.
4. Ejedegba Emmanuel Ochuko. Advancing green energy transitions with eco-friendly fertilizer solutions supporting agricultural sustainability. *Int Res J Mod Eng Technol Sci.* 2024 Dec;6(12):1970. Available from: https://www.doi.org/10.56726/IRJMETS65313
5. Chukwunweike J. Design and optimization of energy-efficient electric machines for industrial automation and renewable power conversion applications. *Int J Comput Appl Technol Res*. 2019;8(12):548–560. doi: 10.7753/IJCATR0812.1011.
6. Wang S, Chen S, Zhou J, Zhang H, Fan Y, Tu C. Uncovering Multidimensional Drivers of Global Food Exports: A Nonlinear Causal Analysis Using Convergent Cross Mapping. Available at SSRN 5262421.

7. Odeniran OM. Exploring the Potential of Bambara Groundnut Flour as an Alternative for Diabetic and Obese Patients in the USA: A Comprehensive Review. Cureus. 2025 Jan 30;17(1).

8. Chiamaka OT, Alawode A. AI-enhanced scenario planning for US food trade policy: Anticipating global supply chain shocks and food insecurity risks.

9. Ndubuisi AF. Strengthening national cybersecurity policies through coordinated threat intelligence sharing and real-time public-private collaboration frameworks. *Int J Sci Res Arch*. 2023;08(02):812–31. doi: https://doi.org/10.30574/ijsra.2023.8.2.0299.

10. Moledina AA. Exploring the transmission of international and domestic economic shocks to United States agriculture. University of Minnesota; 2002.

11. Ejedegba Emmanuel Ochuko. Synergizing fertilizer innovation and renewable energy for improved food security and climate resilience. *Int J Res Publ Rev.* 2024 Dec;5(12):3073–88. Available from: https://doi.org/10.55248/gengpi.5.1224.3554

12. Chukwunweike Joseph, Salaudeen Habeeb Dolapo. Advanced Computational Methods for Optimizing Mechanical Systems in Modern Engineering Management Practices. *International Journal of Research Publication and Reviews*. 2025 Mar;6(3):8533-8548. Available from: https://ijrpr.com/uploads/V6ISSUE3/IJRPR40901.pdf

13. Zelingher R, Makowski D, Brunelle T. Assessing the sensitivity of global maize price to regional productions using statistical and machine learning methods. Frontiers in Sustainable Food Systems. 2021 Jun 2;5:655206.

14. Chibogwu Igwe-Nmaju. Organizational communication in the age of APIs: integrating data streams across departments for unified messaging and decision-making. *International Journal of Research Publication and Reviews*. 2024 Dec;5(12):2792–2809. Available from: https://ijrpr.com/uploads/V5ISSUE12/IJRPR36937.pdf

15. Gordeev S, Jelliffe J, Kim D, Steinbach S. What matters for agricultural trade? Assessing the role of trade deal provisions using machine learning. Applied Economic Perspectives and Policy. 2023.

16. Aidoo EM. Community based healthcare interventions and their role in reducing maternal and infant mortality among minorities. *International Journal of Research Publication and Reviews*. 2024 Aug;5(8):4620–36. Available from: https://doi.org/10.55248/gengpi.6.0325.1177

17. Tack JB, Ala-Kokko K, Gardner GE, Breneman V, Arita S, Cooper J. Climate-based measures of supply chain resilience. Agricultural Finance Review. 2025 Feb 5.

18. Ndubuisi AF. The impact of international cybersecurity treaties on domestic cybercrime control and national critical infrastructure protection. *World Journal of Advanced Research and Reviews*. 2023;20(3):2285-2304. doi: https://doi.org/10.30574/wjarr.2023.20.3.2549

19. Kampouris I, Mertzanis C, Samitas A. Natural disaster shocks and commodity market volatility: A machine learning approach. Pacific-Basin Finance Journal. 2025 Apr 1;90:102618.

20. Emmanuel Ochuko Ejedegba. INTEGRATED STRATEGIES FOR ENHANCING GLOBAL FOOD SECURITY AMID SHIFTING ENERGY TRANSITION CHALLENGES. International Journal of Engineering Technology Research & Management (ijetrm). 2024Dec16;08(12).

21. Boer L, Rieth M. The macroeconomic consequences of import tariffs and trade policy uncertainty. International Monetary Fund; 2024 Jan 19.

22. Ajayi R. Integrating IoT and cloud computing for continuous process optimization in real-time systems. *Int J Res Publ Rev.* 2025 Jan;6(1):2540–2558. doi:10.55248/gengpi.6.0125.0441.

23. Ugwueze VU, Chukwunweike JN. Continuous integration and deployment strategies for streamlined DevOps in software engineering and application delivery. Int J Comput Appl Technol Res. 2024;14(1):1–24. doi:10.7753/IJCATR1401.1001.

24. Ayala-García J, Ceballos-Sierra F. A Competitor-Based Weighting Matrix for Estimating Trade Spillovers from Supply Shocks. Available at SSRN 5208013.

25. Dorgbefu EA. Leveraging predictive analytics for real estate marketing to enhance investor decision-making and housing affordability outcomes. Int J Eng Technol Res Manag. 2018;2(12):135. Available from: https://doi.org/10.5281/zenodo.15708955.

26. Velasco JM, Chang CL. Adapting Agriculture: Navigating Climate Dynamics in Global Trade. Available at SSRN 4813915.

27. Ejedegba Emmanuel Ochuko. Innovative solutions for food security and energy transition through sustainable fertilizer production techniques. *World J Adv Res Rev.* 2024;24(3):1679–95. Available from: https://doi.org/10.30574/wjarr.2024.24.3.3877

28. Zelingher R. Democratising Agricultural Commodity Price Forecasting: The AGRICAF Approach. arXiv preprint arXiv:2410.20363. 2024 Oct 27.

29. Ajayi R, Adedeji BS**.** Neural network-based face detection for emotion recognition in mental health monitoring. *Int J Res Publ Rev.* 2024 Dec;5(12):4945–4963.

30. Kuhla K, Kubiczek P, Otto C. Understanding agricultural market dynamics in times of crisis: The dynamic agent-based network model Agrimate. Ecological Economics. 2025 May 1;231:108546.

31. Ajayi R, Masunda M. Integrating edge computing, data science and advanced cyber defense for autonomous threat mitigation. *Int J Sci Res Arch.* 2025 May;15(2):63–80. doi:10.30574/ijsra.2025.15.2.1292.

32. Li X. Economic Impact of China's Retaliatory Soybean Tariff on US Soybean Farmers. arXiv preprint arXiv:2503.10715. 2025 Mar 13.

33. Dorgbefu EA. Driving equity in affordable housing with strategic communication and AI-based real estate investment intelligence. *International Journal of Computer Applications Technology and Research.* 2019;8(12):561–74. Available from: https://doi.org/10.7753/IJCATR0812.1012

34. Batarseh FA, Gopinath M, Monken A, Gu Z. Public policymaking for international agricultural trade using association rules and ensemble machine learning. Machine Learning with Applications. 2021 Sep 15;5:100046.

35. Adjemian M, Petroff C, Robe MA. The political economy of export bans and commodity price volatility: Theory and evidence from agricultural markets. SSRN; 2022 Dec.

36. Raymond Antwi Boakye, George Gyamfi, Cindy Osei Agyemang. DEVELOPING REAL-TIME SECURITY ANALYTICS FOR EHR LOGS USING INTELLIGENT BEHAVIORAL AND ACCESS PATTERN ANALYSIS. International Journal of Engineering Technology Research & Management (IJETRM). 2023Jan21;07(01):144–62.

37. Nes K, Schaefer KA, Gammans M, Scheitrum DP. Extreme weather events, climate expectations, and agricultural export dynamics. American Journal of Agricultural Economics. 2025.

38. Bandarupalli G. Machine learning-driven analysis of the economic impact of current US trade tariffs on global supply chains. Authorea Preprints. 2025.

39. Ajayi R. Computerizing Kaduna Polytechnic staff record management and posting information system. 2007 Aug. doi:10.13140/RG.2.2.16000.14086

40. Kiparisov P, Folberth C. Modeling impacts of food and fertilizer trade disruptions on global food security.

41. Chukwunweike J, Lawal OA, Arogundade JB, Alade B. Navigating ethical challenges of explainable AI in autonomous systems. *International Journal of Science and Research Archive*. 2024;13(1):1807–19. doi:10.30574/ijsra.2024.13.1.1872. Available from: https://doi.org/10.30574/ijsra.2024.13.1.1872.

42. Arita S, Steinbach S, Zhuang X. NDSU Agricultural Trade Monitor 2025-06.

43. Dorgbefu EA. *Translating complex housing data into clear messaging for real estate investors through modern business communication techniques.* International Journal of Computer Applications Technology and Research. 2018;07(12):485–499. Available from: https://doi.org/10.7753/IJCATR0712.1010

44. Gopinath M. Does trade policy uncertainty affect agriculture?. Applied Economic Perspectives and Policy. 2021 Jun;43(2):604-18.

45. Agyemang CO, Boakye RA, Gyamfi G. Data-Driven Medicaid Reform to Advance Equitable Healthcare Access for Immigrant Populations Across U.S. States. *Int J Adv Res Publ Rev.* 2025 May;2(5):252–73.

46. Antràs P, Zilberman D, editors. Risks in Agricultural Supply Chains. University of Chicago Press; 2023 Sep 13.

47. Mukasa AL, Makandah EA. Hybrid AI-driven threat hunting and automated incident response for financial security in U.S. healthcare. *Int J Comput Appl Technol Res*. 2021;10(12):293–309.

48. Naqvi SA. Global demand and supply elasticities and the impact of tariff shocks. WIFO Working Papers; 2025.

49. Agyemang CO, Boakye RA, Gyamfi G. Leveraging health data analytics to drive inclusive Medicaid expansion and immigrant healthcare policy reform. *Int J Comput Appl Technol Res.* 2025;14(6):1–18. doi:10.7753/IJCATR1406.1001.

50. Srishti V, Xin Z, Vyacheslav L. Impacts of extreme weather stress and synchronous yield fluctuation on the international wheat trade network. Authorea Preprints. 2022 Nov 16.

51. Enuma Edmund. Implementing customer-identity management to combat SIM-card fraud: a security framework for emerging market telcos. *Int J Comput Appl Technol Res*. 2017;6(12):533–49. Available from: https://doi.org/10.7753/IJCATR0612.1011

52. Vishwakarma S, Zhang X, Lyubchich V. Impacts of extreme weather stress and synchronous yield fluctuation on the international wheat trade network. Authorea Preprints. 2023 Jan 20.

53. Odumbo OR. Explainable AI and Federated Learning in Healthcare Supply Chain Intelligence: Addressing Ethical Constraints, Bias Mitigation, and Regulatory Compliance for Global Pharmaceutical Distribution. *International Journal of Computer Applications Technology and Research*. 2025;14(4):16–29. doi:10.7753/IJCATR1404.1002.

54. Goyal R, Steinbach S, Yildirim Y, Zhuang X. US Agricultural Trade Challenges Amid Climate and Geopolitical Disruptions. Choices. 2024 Jul 1;39(3):1-7.