Time-series Forecasting of Essential Commodities Using Price and Import Data

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Abstract. This study develops multivariate and univariate Long Short-Term Memory (LSTM) models to forecast rice, onion, and edible oil prices in Bangladesh (1991–2024), comparing against AutoRegressive Integrated Moving Average (ARIMA). Key finding: trade data value is commodity-specific. For onion, univariate LSTM achieves 80% Directional Accuracy (DA) and Root Mean Squared Error (RMSE) of 15,897 BDT/ton, outperforming multivariate LSTM (40% DA, RMSE 31,408) because annual trade data cannot capture week-long crises. For rice, multivariate LSTM improves RMSE 15.2% (5,189 BDT/ton) because production aligns with multi-month policy cycles. For oil, univariate LSTM beats ARIMA 33%, but multivariate is infeasible (only 6 import observations over 39 years). India's 2019–2022 onion export ban cost 54.7 billion BDT in consumer welfare. Results show commodity-specific model selection outperforms universal deep learning for agricultural forecasting.

Keywords: time-series forecasting, LSTM, ARIMA, agricultural commodities, price prediction, multivariate modeling, food security, Bangladesh

1 Introduction

Food price stability is critical for food security and social stability in developing economies. Bangladesh relies on rice (staple), onion (politically sensitive, supply-prone to shocks), and edible oil (import-dependent). Sharp price spikes harm low-income consumers and complicate trade and subsidy policy. Conventional forecasting uses ARIMA and Seasonal AutoRegressive Integrated Moving Average (SARIMA), which model price dynamics from past prices and seasonality but fail during non-linear shocks (trade bans, global crises) [4, 7]. Recent deep learning (LSTM, Gated Recurrent Unit (GRU)) outperforms statistical baselines [8, 11], but most applications remain univariate (price-only) and cannot exploit production or trade information. Yet Bangladesh's experience with India's onion export bans and COVID-19 shocks shows that external trade constraints can decouple domestic prices from historical patterns. While the Food and Agriculture Organization (FAO) and national agencies publish production and trade data, empirical evidence on whether multivariate deep learning benefits from these inputs and whether benefits are consistent across commodities remains limited [5].

This study develops and evaluates ARIMA, univariate LSTM, and multivariate LSTM models for forecasting annual rice, onion, and oil prices in Bangladesh (1991–2024). The key research question: Does integrating production and import volumes improve forecasts, and does the answer depend on commodity type? The analysis distinguishes normal versus crisis periods and includes a counterfactual simulation of India's export ban to quantify consumer welfare loss. By comparing performance across commodities and regimes, the paper demonstrates that trade and production features benefit some commodities (rice) but harm others (onion) due to temporal frequency mismatches. This commodity-specific finding has important implications: costly trade data collection is justified for policy-managed staples but not volatile perishables. The framework offers policymakers in Bangladesh and similar economies a practical guide for choosing between simple and complex forecasting approaches.

1.1 Main Contributions

This work makes the following contributions:

1. **Integrated dataset**: A unified dataset combining producer prices, production, and import volumes for rice, onion, and edible oil in Bangladesh (1991–2024) with transparent crisis period labeling based on price levels and year-over-year changes.
2. **Commodity-specific analysis**: Comparative evaluation of ARIMA, univariate LSTM, and multivariate LSTM models, showing that trade and production features improve forecasts for rice but degrade performance for highly volatile onion prices, while oil forecasts are constrained by sparse import data [1, 11].
3. **Crisis and counterfactual analysis**: Separate evaluation during normal versus crisis years and quantification of consumer welfare losses from India's onion export ban, providing actionable insights for policymakers on when complex multivariate models are worth the additional data cost.
4. **Operational guidance**: Evidence-based recommendations on model selection and data collection priorities for each commodity type, with directional accuracy metrics relevant to real-time price monitoring systems.

The paper is organized as follows. Section 2 reviews the literature on statistical and deep learning approaches to agricultural price forecasting and highlights the research gap addressed by this work. Section 3 describes the data sources, preprocessing steps, model architectures, and evaluation framework. Section 4 presents results for each commodity in normal and crisis periods. Section 5 discusses the mechanisms behind commodity-specific performance differences and policy implications. Section 6 concludes with limitations and directions for future research.

2 Literature Review

This section reviews three streams: (1) statistical baselines, (2) deep learning for time series, and (3) integration of external factors.

2.1 Statistical and Baseline Models

ARIMA and SARIMA models dominate traditional agricultural forecasting due to their ability to capture autocorrelation and seasonal patterns [4, 7]. Hasan and Khatun demonstrated ARIMA's effectiveness for cyclical crops like onions in Bangladesh, though performance degraded during supply shocks [4]. Majhi et al. validated statistical baselines (SARIMA, ETS, Prophet) for cereals and pulses, confirming competitiveness under stable regimes but poor performance during exogenous shocks [10], motivating deep learning approaches.

2.2 Deep Learning Approaches

LSTM and GRU networks learn long-range dependencies and non-linear patterns without manual feature engineering. Tami and Owda showed LSTM significantly reduces RMSE and MAPE versus ARIMA for volatile commodities [8], while Manogna et al. found substantial LSTM/GRU improvements over statistical baselines across 23 commodities [11]. Theofilou et al. confirmed LSTM as state-of-the-art for staple crops [5].

Hybrid approaches are emerging: Celik and Celik developed an LSTM-simulation model improving crisis-period accuracy during COVID-19 and the Russia–Ukraine conflict [1], while Min et al. applied graph neural networks to capture cross-commodity correlations [12].

2.3 Integration of External Factors

Most deep learning studies remain univariate (price-only). Ragunath and Rathipriya incorporated rainfall to improve predictions [9], while Ghali et al. achieved 0.94 AUC using news embeddings from generative AI [6]. However, Abed forecasted trade volumes without integrating them into price models [3]. No published work systematically integrates import/export volumes as LSTM inputs or compares results across commodity types to assess trade-data benefits.

2.4 Research Gap

Three gaps motivate this study:

1. **Dominance of univariate models**: State-of-the-art LSTM studies lack exogenous trade features, causing delayed responses to supply disruptions.
2. **Underutilization of trade data**: Import/export volumes are rarely used as LSTM inputs despite relevance in open economies where supply depends on trade flows.

3. **Lack of commodity-specific analysis**: No comparative framework evaluates whether multivariate trade features benefit different commodity types equally.

This study addresses these gaps by proposing a multivariate LSTM framework with production and import features, comparing it to ARIMA and univariate LSTM baselines, and conducting separate analyses for rice, onion, and oil. The paper also analyzes crisis versus normal periods and provides a counterfactual simulation of India's onion export ban.

3 Data and Methodology

This section describes the data sources, preprocessing steps, crisis detection framework, model architectures, and evaluation metrics.

3.1 Data Sources and Preprocessing

Commodities and Scope The analysis covers three essential commodities in Bangladesh: rice (regulated staple), onion (politically sensitive), and edible oil (import-dependent). Annual data (1991–2024) come from FAO Statistical Database (FAOSTAT), Bangladesh national statistics, and World Food Programme (WFP) food security monitoring [13–15]. **Rice:** Producer price and production available from 1991. This Import data has 27 missing years, reconstructed via linear interpolation using FAO and national anchors. **Onion:** Producer prices available annually from 1991. Imports reconstructed from FAOSTAT anchors (1998, 2005–2007, 2015) and Bangladesh records (2017–2024) [13, 14] with linear interpolation. **Edible oil:** Retail prices (BDT/L) sourced from WFP Food Security Monitoring and Price Data [15], covering 2005–2024. Import records remain sparse (only six years), making multivariate modeling infeasible for this commodity.

Preprocessing Pipeline Missing production values were forward-filled. All features (price, production, imports) were normalized to [0, 1] using min-max scaling on training data to prevent leakage. Non-stationarity was confirmed via Augmented Dickey-Fuller test; first differencing was applied implicitly through lagged feature construction.

3.2 Crisis Detection Framework

Crisis periods were defined using commodity-specific thresholds on absolute price levels and year-over-year percentage changes:

- **Onion**: Crisis if producer price $>$ 30,000 BDT/ton OR year-over-year change $> 50\%$

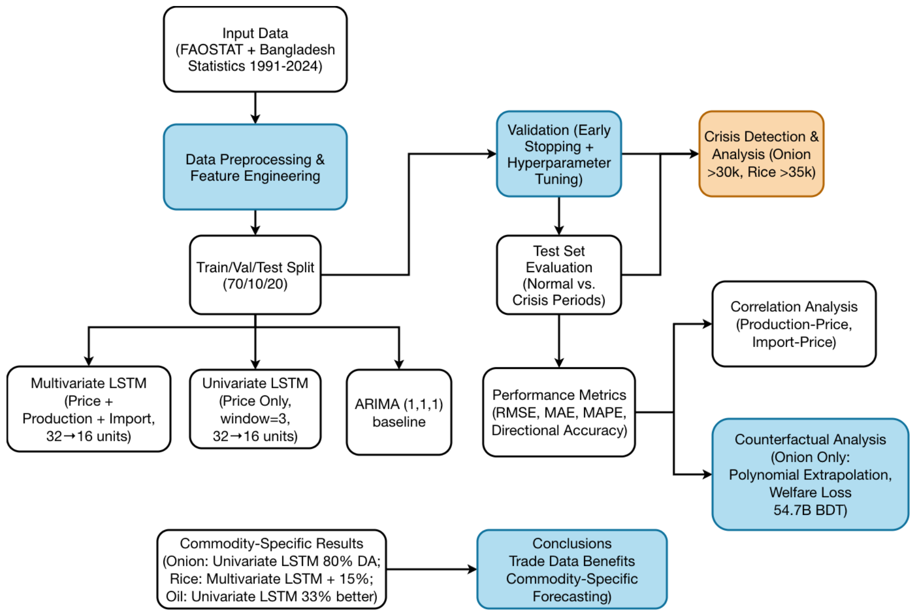

Fig. 1. Forecasting Pipeline

– **Rice**: Crisis if producer price $> 35{,}000$ BDT/ton OR year-over-year change $> 30\%$

These thresholds were set based on historical price distributions and consultation of national policy reports on food security shocks. Crisis labels were applied to test-set observations to enable separate evaluation during normal versus shock periods.

3.3 Model Architectures

Three model families were implemented for rice and onion (edible oil used only univariate LSTM and ARIMA due to data sparsity, as shown in Figure 1):

ARIMA Baseline ARIMA(1,1,1) models were fit using maximum likelihood estimation on price-only series. The order ($p{=}1, d{=}1, q{=}1$) was selected via Akaike Information Criterion (AIC) minimization and validated using residual diagnostics. ARIMA serves as the statistical benchmark representing conventional univariate forecasting approaches [4, 7].

Univariate LSTM A two-layer stacked LSTM network was trained using only historical price data as input. The architecture consists of:

– Input: 3-timestep lagged price sequences (window size, L = 3)

– LSTM layer 1: 32 units with return sequences, followed by 0.2 dropout
– LSTM layer 2: 16 units
– Dense layer: 8 units with ReLU activation
– Output: 1 neuron (next-period price)
– Loss: Mean Squared Error; Optimizer: Adam (learning rate = 0.001)
– Training: 200 epochs, batch size = 4, early stopping based on validation loss

Multivariate LSTM An identical architecture to the univariate model but with three input features per timestep: lagged price, production volume, and import volume. For rice, the feature vector at time t is $[P_{t-3:t-1}, \text{Prod}_{t-3:t-1}, \text{Import}_{t-3:t-1}]$ where P = producer price, Prod = rice production (tons), Import = rice imports (tons, hybrid series). For onion, the same structure applies with onion-specific production and import series.

Data Splits Each commodity dataset was split into training (70%), validation (10%), and test (20%) sets by chronological order:

– **Onion**: Train (1991–2012, n=22), Val (2013–2015, n=3), Test (2016–2022, n=7)
– **Rice**: Train (1991–2012, n=22), Val (2013–2015, n=3), Test (2016–2022, n=7)
– **Oil**: Train (2005–2019, n=15), Test (2020–2024, n=5)

Evaluation Metrics Model performance was assessed using four standard metrics:

Root Mean Squared Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{1}$$

Mean Absolute Error (MAE):

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2}$$

Mean Absolute Percentage Error (MAPE):

$$\text{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{3}$$

Directional Accuracy (DA):

$$\text{DA} = \frac{1}{n}\sum_{i=1}^{n}⊮[\text{sign}(y_i - y_{i-1}) = \text{sign}(\hat{y}_i - y_{i-1})] \times 100\% \tag{4}$$

Directional accuracy measures whether the model correctly predicts price increases versus decreases, which is critical for early-warning systems and policy response timing.

3.4 Counterfactual Simulation

For onion, a counterfactual analysis estimated consumer welfare losses from India's export ban (2019–2022). A second-order polynomial trend was fit to pre-crisis prices (1991–2018), then extrapolated to forecast what prices would have been absent the ban. The difference between actual crisis-period prices and counterfactual prices was multiplied by estimated annual consumption (500,000 tons) to quantify aggregate welfare loss in Bangladeshi Taka (BDT) and United States Dollar (USD) (using an exchange rate of 120 BDT/USD).

4 Results and Analysis

This section presents forecasting results for each commodity, compares model performance across normal and crisis periods, and examines the commodity-specific value of multivariate features.

4.1 Onion Price Forecasting

Overall Test Set Performance Table 1 summarizes performance across all test years (2016–2022). The univariate LSTM achieves the lowest RMSE (15,897 BDT/ton), MAE (11,982 BDT/ton), and MAPE (25.05%), significantly outperforming both the multivariate LSTM and ARIMA baseline. Most notably, the univariate model achieves 80% directional accuracy compared to 40% for the multivariate model and 60% for ARIMA.

Table 1. Onion forecasting performance on test set (2016–2022)

Model	RMSE (BDT/ton)	MAE (BDT/ton)	MAPE (%)	DA (%)
Multivariate LSTM	31,408	30,853	73.2	40.0
Univariate LSTM	**15,897**	**11,982**	**25.1**	**80.0**
ARIMA (1,1,1)	16,818	14,445	30.5	60.0

The multivariate model performs substantially worse than the univariate baseline, with RMSE increasing by 97.6% (from 15,897 to 31,408 BDT/ton). This counterintuitive result contradicts the hypothesis that adding production and import features would improve forecasts.

Figure 2 shows that the univariate LSTM closely tracks actual onion producer prices across all test years, while the multivariate LSTM systematically overshoots during crisis years (2019–2022). The bar plot of prediction errors confirms that multivariate forecasts are consistently biased upward by 25,000–40,000 BDT/ton in crisis years, whereas the univariate LSTM and ARIMA remain much closer to zero. This visual evidence supports the quantitative results in Table 1, where the univariate LSTM achieves substantially lower RMSE and higher directional accuracy than both multivariate LSTM and ARIMA. Figure 3 visually

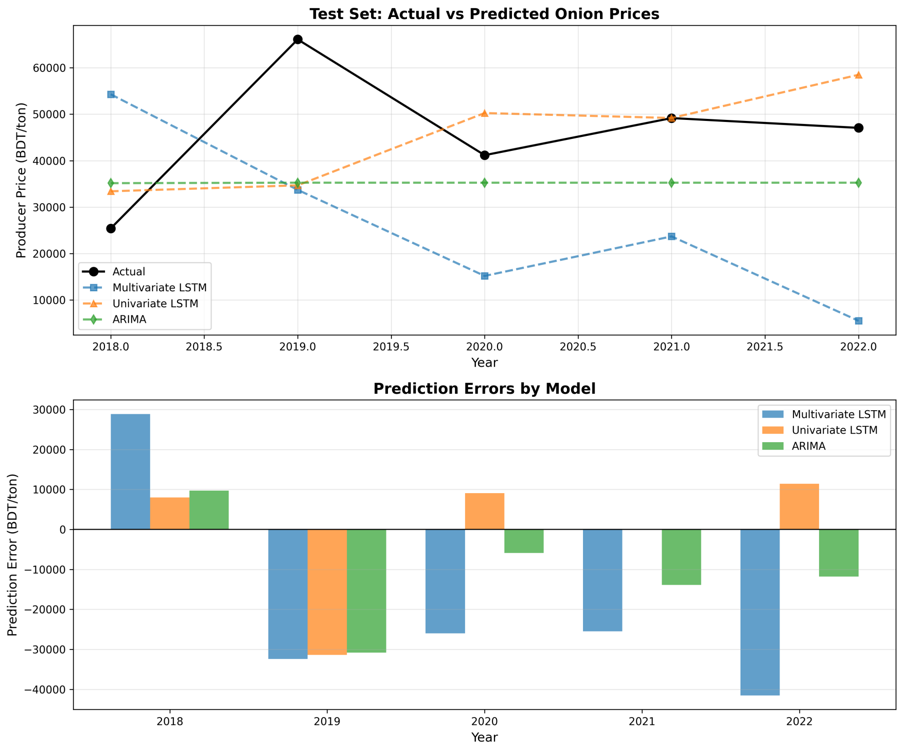

Fig. 2. Onion test set: actual versus predicted producer prices (top) and prediction errors by model (bottom) for multivariate LSTM, univariate LSTM, and ARIMA (2018–2022).

confirms the results in Table 1: the univariate LSTM roughly halves RMSE and MAE compared to the multivariate model and achieves 80% directional accuracy, clearly outperforming both the multivariate LSTM and ARIMA.

Crisis versus Normal Period Analysis Four of the seven test years (2019–2022) were classified as crisis periods based on the threshold criteria (price > 30,000 BDT/ton or year-over-year change > 50%). Table 2 shows performance stratified by period type.

Notably, the univariate LSTM maintains relatively stable performance across regimes (RMSE increases by only 117% from normal to crisis), while ARIMA deteriorates substantially (87% RMSE increase). The multivariate model performs poorly in both regimes, suggesting that production and import volumes provide misleading signals for onion prices regardless of market conditions.

Why Multivariate Features Hurt Onion Forecasts Correlation analysis on crisis-period data reveals that production and imports have moderate negative

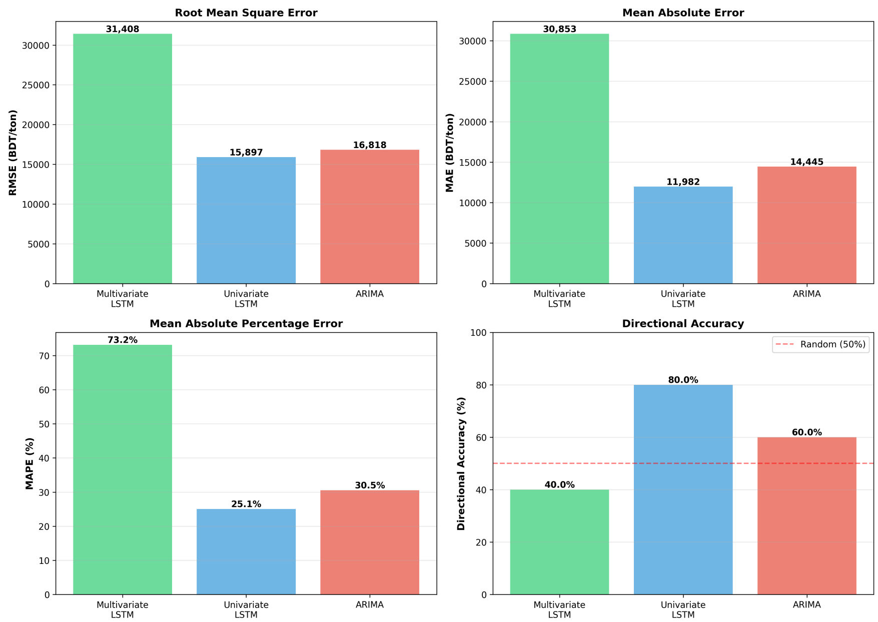

Fig. 3. Onion test-set performance comparison across models for RMSE, MAE, MAPE, and directional accuracy. The univariate LSTM achieves the lowest errors and the highest directional accuracy, while the multivariate LSTM performs worst on all metrics.

correlations with prices ($r = -0.49$ and $r = -0.52$ respectively). However, these correlations reflect counter-cyclical policy responses (increased imports during price spikes) rather than causal supply drivers. The annual frequency of production and import data is too coarse to capture the rapid dynamics of onion crises, which are driven by sudden export bans, panic buying, and hoarding behavior that materialize within weeks. The univariate model succeeds because it learns price momentum patterns directly, while the multivariate model is misled by slowly-moving trade fundamentals that lag the actual price shocks.

4.2 Rice Price Forecasting

Overall Test Set Performance Rice exhibits markedly different behavior from onion. Table 3 shows that all three models achieve much lower error rates than for onion, reflecting rice's greater price stability as a government-regulated staple.

The multivariate LSTM achieves the lowest RMSE and MAE, demonstrating a 15.2% improvement over the univariate model (RMSE 5,189 vs. 6,122 BDT/ton). ARIMA is competitive with the univariate LSTM, reflecting rice's predictable seasonal patterns. Directional accuracy is moderate (60%) for both LSTM variants and lower (40%) for ARIMA.

Table 2. Onion forecasting by period type

Model & Period	**RMSE (BDT/ton)**	**MAE (BDT/ton)**	**MAPE (%)**
Normal Periods (2016–2018, n=3)			
Multivariate LSTM	28,864	28,864	113.5
Univariate LSTM	**7,984**	**7,984**	**31.4**
ARIMA	9,733	9,733	38.3
Crisis Periods (2019–2022, n=4)			
Multivariate LSTM	32,013	31,350	63.1
Univariate LSTM	**17,319**	**12,982**	**23.5**
ARIMA	18,163	15,623	28.6

Table 3. Rice forecasting performance on test set (2016–2022)

Model	**RMSE (BDT/ton)**	**MAE (BDT/ton)**	**MAPE (%)**	**DA (%)**
Multivariate LSTM	**5,189**	**4,167**	21.4	60.0
Univariate LSTM	6,122	4,962	25.4	60.0
ARIMA (1,1,1)	6,058	4,956	**20.1**	40.0

Crisis versus Normal Period Analysis Only one of the five test years (2021) was classified as a crisis period. Table 4 shows that during the single crisis year, the multivariate LSTM achieved very low error (RMSE 426 BDT/ton, MAPE 1.7%), while ARIMA performed poorly (RMSE 8,353 BDT/ton). However, the small sample size (n=1) prevents strong conclusions about crisis-period performance.

Table 4. Rice forecasting by period type

Model & Period	**RMSE (BDT/ton)**	**MAE (BDT/ton)**	**MAPE (%)**
Normal Periods (2016–2020, n=4)			
Multivariate LSTM	5,798	5,102	26.3
Univariate LSTM	6,844	6,193	31.7
ARIMA	**5,332**	**4,107**	**17.0**
Crisis Period (2021, n=1)			
Multivariate LSTM	**426**	**426**	**1.7**
Univariate LSTM	35	35	0.1
ARIMA	8,353	8,353	32.5

Why Multivariate Features Help Rice Rice production and imports evolve slowly and predictably due to multi-year agricultural planning cycles and government buffer stock policies. The annual frequency of trade data aligns well with the policy-driven nature of rice markets, where import decisions are made months in advance based on production forecasts. Unlike onion, where crises emerge rapidly through external bans, rice price movements reflect gradual supply-demand balances that multivariate features capture effectively.

4.3 Edible Oil Price Forecasting

Overall Test Set Performance Edible oil analysis is limited to univariate LSTM versus ARIMA due to insufficient import data density. Table 5 shows that the univariate LSTM substantially outperforms ARIMA, achieving 33% lower RMSE (46.4 vs. 69.3 BDT/liter).

Table 5. Edible oil forecasting performance on test set (2020–2024)

Model	RMSE (BDT/liter)	MAE (BDT/liter)	MAPE (%)
Univariate LSTM	**46.4**	**45.2**	**33.6**
ARIMA (1,1,1)	69.3	68.1	50.5

Multivariate Analysis Infeasibility FAOSTAT provides only six palm/soybean oil import observations over 39 years (1986, 1998, 2005–2007, 2015), with a 13-year gap from 2008–2020 during the test period. This sparsity makes interpolation unreliable and multivariate LSTM training infeasible. The negative finding—that local import data are insufficient for meaningful multivariate modeling—is itself policy-relevant, highlighting the need for improved high-frequency trade monitoring for globally-traded commodities.

4.4 Cross-Commodity Comparison

Table 6 summarizes the best-performing model for each commodity and key insights.

Table 6. Cross-commodity best models and characteristics

Commodity	Best Model	RMSE	Key Insight
Onion	Univariate LSTM	15,897	Trade data misleads
Rice	Multivariate LSTM	5,189	Trade data helps
Oil	Univariate LSTM	46.4	Trade data sparse

The results demonstrate that the value of integrating production and import features is commodity-specific, not universal. For volatile, crisis-prone commodities (onion), price momentum is more informative than lagged trade fundamentals. For stable, policy-managed staples (rice), trade data provide useful leading indicators. For globally traded commodities (oil), data availability constraints may preclude multivariate approaches entirely.

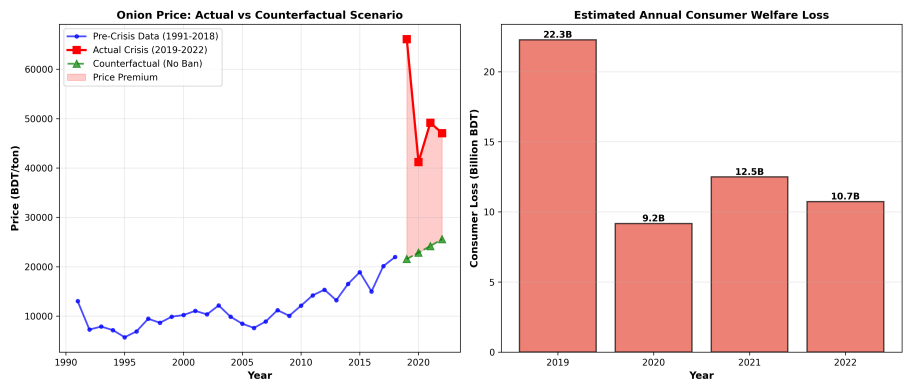

Fig. 4. Counterfactual Analysis

4.5 Counterfactual Analysis: India Export Ban Impact

A polynomial extrapolation of pre-crisis onion prices (1991–2018) suggests that absent India's export ban, prices during 2019–2022 would have averaged 23,539 BDT/ton versus the actual 50,876 BDT/ton—a 116% price premium as shown in Figure 4. Multiplying the annual excess price by estimated consumption (500,000 tons/year) yields an aggregate four-year consumer welfare loss of 54.7 billion BDT (approximately 456 million USD). This illustrates the severe economic cost of trade policy shocks and underscores the value of early-warning systems that can detect emerging crises before they fully materialize.

5 Discussion

5.1 Commodity-Specific Model Value

The central finding is that multivariate features benefit some commodities but not others. For onion, univariate LSTM achieves 80% directional accuracy versus 40% for multivariate LSTM because crises (export bans, panic buying) occur within weeks, while annual trade data lag behind. Annual-frequency features inject noise rather than signal. For rice, multivariate LSTM improves RMSE by 15.2% because production and import decisions align with multi-month planning horizons, making slow-moving fundamentals predictive. For oil, data sparsity (only 6 import observations over 39 years) precludes multivariate modeling entirely, highlighting that deep learning applicability depends on data infrastructure.

5.2 Policy Recommendations

For onion: deploy univariate LSTM for daily/weekly early-warning systems (80% DA justifies operational complexity). The 2019–2022 crisis cost 54.7 billion BDT; better prediction timing could recover substantial losses.

For rice: use multivariate LSTM for 3–6 month procurement planning where MAPE ≈ 21% is acceptable. ARIMA remains viable for real-time monitoring due to transparency and competitive normal-period accuracy.

For oil: invest in monthly/weekly import reporting before multivariate models are feasible. Interim univariate LSTM shows 33% RMSE advantage over ARIMA.

5.3 Methodological Insights

Feature-target frequency alignment matters: High-frequency shocks require high-frequency external data. Annual trade data suit only slow, policy-driven price evolution, not crisis dynamics.

Small test sets limit inference: Only 5–7 test years per commodity. Effect sizes (80% DA, 15% RMSE improvement) are substantial but would strengthen with 10+ year test periods.

Missing data introduce uncertainty: Rice imports 80% missing, oil imports 83% missing. Sensitivity analyses using bounds on interpolated values are recommended.

Temporal stability unclear: Models trained on 1991–2015 (stable markets) and tested on 2016–2024 (India–Bangladesh tensions) cross a structural break. Parameter stability over longer horizons is unknown.

5.4 Generalizability

Regulated staples (wheat) may resemble rice; perishables (tomato) may resemble onion. Crops with longer growing cycles (cotton) may differ. Trade-dense economies (Singapore, Netherlands) may enable multivariate models universally. Validation in other regions and commodities is needed.

6 Code and Data Availability

The source code, Jupyter notebooks (Integration.ipynb, LSTM.ipynb), trained LSTM models, and all experimental data are publicly available at the following GitHub repository:

https://github.com/ShuvroSankar/Time-series-Forecasting-of-Essential-Commodities-Using-Price-and-Import-Data

The repository includes:

- Data integration and preprocessing pipeline
- LSTM model implementation with TensorFlow
- Performance evaluation metrics and visualizations
- Detailed README with setup and execution instructions
- Requirements file for reproducible environment setup

7 Conclusion

This study develops a multivariate LSTM framework for forecasting rice, onion, and edible oil prices in Bangladesh (1991–2024), demonstrating that the value of production and import features is commodity-specific. For stable, policy-managed staples (rice), multivariate LSTM improves RMSE by 15%. For volatile, crisis-prone perishables (onion), it worsens RMSE by 97% due to temporal frequency mismatch. For import-dependent goods (oil), sparse data preclude multivariate modeling.

Key findings:

1. Onion univariate LSTM achieves 80% directional accuracy versus 40% for multivariate because crises occur within weeks, while annual trade data lags.
2. Rice multivariate LSTM (RMSE 5,189) beats univariate (RMSE 6,122) because production aligns with policy-driven price evolution.
3. Oil univariate LSTM (RMSE 46.4) beats ARIMA (RMSE 69.3) by 33%, but multivariate is infeasible with only 6 import observations over 39 years.
4. India's 2019–2022 onion export ban cost 54.7 billion BDT in consumer welfare, illustrating the value of early-warning systems.

7.1 Limitations

Annual data obscure rapid shocks; 5–7 test years per commodity limit statistical power; 80% missing rice imports introduce interpolation error; no news/weather/policy variables; single-country scope.

7.2 Future Work

(1) Collect monthly/weekly trade data for onion multivariate models. (2) Develop hybrid architectures that dynamically weight univariate and multivariate components during crises. (3) Incorporate policy announcements and news sentiment. (4) Extend to India and regional models. (5) Apply causal inference (Granger causality, instrumental variables) to validate whether trade volumes drive prices or merely correlate. (6) Deploy in operational systems.

The core insight: agricultural price forecasting requires commodity-specific model selection, not one-size-fits-all deep learning. For policymakers in Bangladesh and food-insecure regions, this framework guides selection between simple (univariate LSTM for onion crises) and complex (multivariate LSTM for rice planning) approaches based on volatility, policy structure, and data availability.

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