Research Article

Time Series Predicting Analysis of Rapeseed-Mustard Production in Bangladesh: A Strategic Approach Towards Self-Sufficiency in Edible Oil

Mahadi Hasan Monshi[1,2], Muntarina Hussan Mouri[2,3], Rehenuma Tabassum[3], Jahidul Hassan[4], Md. Shakhawat Hossain[5], Md. Sarowar Alam[6], Ahmed Khairul Hasan[5] and Fakhrul Islam Monshi[7]*

[1]Department of Economics, University of Chittagong, Chittagong-4331, Bangladesh; [2]Green Care Agro Farm Ltd., Debidwar, Comilla-3530, Bangladesh; [3]Department of Crop Botany and Tea Production Technology, Sylhet Agricultural University, Sylhet-3100, Bangladesh; [4]Department of Horticulture, Gazipur Agricultural University, Gazipur -1706, Bangladesh; [5]Department of Agronomy, Bangladesh Agricultural University, Mymensingh-2202, Bangladesh; [6]Regional Agricultural Research Station, Bangladesh Agricultural Research Institute (BARI), Akbarpur, Moulvibazar-3210, Bangladesh; [7]Department of Genetics and Plant Breeding, Sylhet Agricultural University, Sylhet-3100, Bangladesh.

Abstract | The increasing gap between local edible oil production and consumption in Bangladesh poses a significant threat to national food security, especially in light of global supply chain disruptions and climatic uncertainty. This research utilizes Autoregressive Integrated Moving Average (ARIMA) models to predict long-term changes in rapeseed-mustard production area, production, consumption, and imports from 2025 to 2039 using collected data from 1964 to 2024. Time series diagnostics, including logarithmic transformation, differencing, and stationarity assessments using Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests, confirmed model validity, while optimal ARIMA parameters were established based on AIC, BIC, and residual diagnostics. Ljung-Box and Jarque-Bera tests were employed to identify autocorrelation. The metrics Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Scaled Error (MASE), and Mean Absolute Percentage Error (MAPE) were applied to verify values. The selected ARIMA models showed strong predictive accuracy, with MAE values of [0.06, 0.08, 0.11, 0.50], RMSE [0.11, 0.13, 0.15, 0.73], MASE [0.97, 0.94, 0.96, 0.95], and MAPE [1.06, 1.49, 1.87, 14.87], indicating reliable forecasting of rapeseed–mustard area, production, consumption, and imports in Bangladesh. Subsequently reviewing all criteria, ARIMA (1,1,1) was identified for the harvested area, ARIMA (0,1,1) for consumption, ARIMA (0,1,1) for production and ARIMA (2,1,0) for imports. These findings suggest a continuous rise in consumption, surpassing output growth and markedly increasing future reliance on imports. Despite slight improvements in domestic output, the core imbalance between supply and demand is expected to intensify, driven by rising population pressures and evolving dietary preferences. The anticipated findings highlighted the pressing necessity for strategic measures, including investment in high-yielding and climate-resilient genotypes, modifications in input subsidies, and targeted oilseed development projects to enhance domestic self-sufficiency and alleviate international market volatility. The research offered a framework for policymakers and development planners to forecast oilseed sector and implement sustainable agricultural strategies aligned with persistent food security.

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***Correspondence** | Fakhrul Islam Monshi, Department of Genetics and Plant Breeding, Sylhet Agricultural University, Sylhet-3100, Bangladesh; **Email:** monshifi.gpb@sau.ac.bd
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Introduction

The functional stability of the global food system is under intensifying multidimensional stress. Multi-layered risks emerging from anthropogenic climate change, geopolitical asymmetries, demographic expansion, and ecological degradation are not only disturbing supply chains but also revealing deep structural vulnerabilities in primary agricultural production and international commerce frameworks (Wezel *et al*., 2020; Fan *et al*., 2024). Amid these intricate global transformations, edible oil markets crucial for human nutrition, household food security, and macroeconomic stability have faced significant threats (Sun *et al*., 2024). Food systems in import-dependent nations of South Asia are more susceptible due to these vulnerabilities, impacting the entire social and economic frameworks (Fan *et al*., 2024).

Bangladesh demonstrates the fragile convergence of escalating consumption patterns and imports dependency driven by demographic pressures and agro-climatic variability (Jannat *et al*., 2022). Despite advantageous agro-ecological conditions and a deep-rooted agricultural heritage, the nation imports about 90% of its domestic supply of edible oil, mainly soybean and palm oil, obtained from extremely volatile global markets (USDA, 2025). This persistent reliance has made the national food system very susceptible to global price variations, currency fluctuations, and supply chain interruptions, intensified by recent crises including the COVID-19 epidemic and the Russia-Ukraine conflict (Ben Hassen and El Bilali, 2022; Urak *et al*., 2024). The global macroeconomic fluctuations have impacted the balance of payments, increased food prices, and heightened nutritional vulnerability among at-risk populations (Sun *et al*., 2024; Monshi *et al*., 2026a). Systemic shocks from international markets have disrupted the national balance of payments, augmented market instability, caused food price inflation, and exacerbated nutritional insecurity (Tchonkouang *et al*., 2024).

Unexpectedly, although Bangladesh has attained outstanding progress toward cereal crop self-sufficiency, its oilseed production remains on the periphery of agricultural priorities, both in terms of policy prioritization and investment flows (Barois *et al*., 2024; Mouri *et al*., 2026a). Among the underutilized alternatives, rapeseed-mustard proposes exceptional strategic potential in oilseed development (Malek *et al*., 2012; Tabassum *et al*., 2015; Islam *et al*., 2022). This is a rapidly developing rabi crop with significant resilience to climatic change, appropriate for intercropping and production on fallow or underused areas (Malek and Monshi, 2009). With low input cost requirements, flexibility across different climatic and soil conditions, and synergy with sustainable intensification frameworks, rapeseed-mustard provides a realistic and ecologically sound alternative to imported edible oils (Monshi and Malek, 2013; Atikunnaher *et al*., 2017). Despite its prospective benefits, widespread adoption is still limited by stagnant yield production, inadequate technical adoption, and the unavailability of consistent market forecasting. Precariously, rapeseed-mustard has been largely neglected in standard economic analyses and strategic forecasting studies, leading to a chronic imbalance between production potential and policy commitment.

Notably, until now, there has been no data-driven study offering a comprehensive, strategic forecast for the future of the rapeseed-mustard sector in Bangladesh, detecting interconnected trajectories of harvested area, production, domestic consumption, and import inflows. Prior studies have predominantly depended on linear projections or narrow-market equilibrium frameworks (Jannat *et al*., 2022; Mila *et al*., 2022), which are inadequate for capturing the autoregressive, non-linear, and fundamental dynamic aspects of agricultural systems under transforming climatic and economic backgrounds. On the other hand, ARIMA models provide a conceptually comprehensive and statistically rigorous technique for single-parameter forecasting, particularly suited to time series analysis exhibiting high temporal autocorrelation, structural shocks, and limited exogenous predictors (Nasir *et al*., 2025; Mila *et al*., 2019; Begum *et al*., 2024; Alsheheri, 2025).

To confront this major gap, the present investigation employed six decades of secondary data (1964-2024) to exploit a set of ARIMA models to project the harvested area, production, consumption, and import trends of rapeseed-mustard in Bangladesh. ARIMA modeling delivers superior flexibility for detecting stochastic variations in temporal data and is universally acknowledged as a dependable approach for projecting agricultural performance under uncertainty (Nasir *et al*., 2025; Shadab *et al*., 2019). Through systematic diagnostic procedures and ratification, the forecasts

formulated in this research strive to provide insights for empirical strategy development for boosting domestic oilseed development, decreasing import dependence alongside eco-friendly farming reforms.

Recognizing the urgent requirement to lower the dependency on imports and mitigate the gap between production and demand for rapeseed, the current study aims to develop and validate ARIMA-based prediction models for rapeseed-mustard production area, production, consumption and imports in Bangladesh. Using historical time-series data, the study offers short-term forecasts that can support policymakers, agribusiness stakeholders, and development planners in formulating responsive strategies to reinforce national rapeseed value chains. Moreover, the research contributes methodologically to flourish academic discourse on statistical modeling in agricultural estimation, offering a basis for future integration with machine learning and hybrid models to expand predictive performance against a backdrop of agro-economic transformation.

Methodology

The technique employed by the ARIMA model is crucial for exact forecasting as it effectively captures trends and temporal patterns in time series data. It offers a comprehensive approach for assessing and estimating the suitable model structure (AR, I, and MA components) derived from the statistical features of the data. This method transforms non-stationary data series into a stationary data series, which is considered as the prerequisite for accurate prediction. It also helps researchers to determine the best model by utilizing diagnostic checks and criteria including AIC, BIC and AICc.

Autoregressive integrated moving average (ARMIA) model

One way of forecasting is the Autoregressive (AR) model, which takes the past values of a time series and uses them to form an estimate of its present value. The basic idea of this assumption is that historical observations impact the present ones. The general AR model with p order was originally proposed by Yule (1926), is defined as:

$$Y_t = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \text{---------} + \varphi_p Y_{t-p} + \epsilon_t$$

Here, Y_t= current observation of the time series, φ_1, φ_2, φ_p = coefficients of the model, Y_{t-1}, Y_{t-2}, Y_{t-p} = lagged observations of the time series ϵ_t = white noise error term with mean zero and constant variance.

On the contrary, a Moving Average (MA) model assesses the present value of a time series incorporating past error terms instead of lagged values. The MA model of order q, pioneer by Slutsky (1927) can be represented as:

$$Y_t = \mu + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \text{-----} + \theta_q \epsilon_{t-q}$$

Here, Y_t = current observation of the time series, μ = mean of the series, ϵ_t = white noise error at time θ_1, θ_2---- θ_q = coefficients of the moving average, q = order of the moving average procedure.

The ARMA (p, q) process comprising lagged observations and past error terms, can be represented mathematically as:

$$Y_t = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \text{---------} + \varphi_p Y_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \text{-----} + \theta_q \epsilon_{t-q}$$

However, in practice, most observed time series are characterized by non-stationarity, indicating the presence of structural patterns or seasonal fluctuations. To effectively describe these patterns, the ARIMA model was employed. The differencing component (d) converts non-stationary series into stationary ones. An ARIMA (p, d, q) model directs that after differentiating the original series d times, the new series follows an ARMA (p, q) technique.
Implementing first-order differencing (d = 1), the series can be redefined as:

$$W_t = Y_t - Y_{t-1}$$

Consequently, the ARIMA (p, 1, q) model can be formulated as:

$$W_{t} = \varphi_1 W_{t-1} + \varphi_2 W_{t-2} + \varphi_p W_{t-p} + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \text{-----} + \theta_q \epsilon_{t-q}$$

Model selection and identification

In the model identification phase of the ARIMA procedure, precise statistical evaluations combined with visual diagnostics were employed to find the best orders of autoregression (p), differencing (d), and moving average (q). Primarily, stationary test was utilized to identify the existence unit root Augmented Dickey-Fuller (ADF) test proposed by Dickey and Fuller (1979) were utilized as outlined below:

$$\Delta y_{t} = \alpha + \beta_{t} + \gamma y_{t-1} + \Sigma^{p}_{i=1} \delta_{i} \Delta y_{t-i} + \varepsilon_{t}$$

To increase estimation accuracy, (KPSS) test were engaged as presented by Kwiatkowski *et al*. (1992), to assess stationarity by testing the null hypothesis of a stationary time series. The KPSS statistic, expressed as

$$KPSS = 1/T \Sigma^{T}_{t-1} St^2/ \sigma^2$$

After identifying and implementing the required differencing order to attain stationarity, the visualization test such as Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots was inspected. The ACF plot identified and prioritized MA mechanisms using substantial autocorrelations at lag values, while the PACF figure ordered AR processes using significant partial autocorrelations.

Model validation and diagnostics

A comprehensive residuals diagnostics were thoroughly examined, to determine the stability and appropriateness of the selected ARIMA model, underscoring the importance of the essential assumptions of normality, independence, and stochastic behavior. The Jarque-Bera (JB) test was examined to inspect the normal distribution of homogeneous residuals by observing both skewness and kurtosis. We can authenticate the normality assumption applying Jarque-Bera (1980) test, which is a goodness of fit measure of divergence from normality, as guided by the sample kurtosis (k) and skewness (s). Ensuring normally distributed residuals is essential for validating model reliability and improving the accuracy and consistency of time-series forecasts. The Jarque–Bera (JB) test was employed to assess the normality of residuals, as it evaluates deviations from normality based on skewness (S) and kurtosis (K), is expressed as:

$$JB = n/6(S^2 + (k-3)^2/4)$$

This was complemented by a visual study of the residuals' histogram, which stipulated an intuitive assessment of their empirical distribution in comparison to the assumed normal curve. Moreover, to ensure that there was no autocorrelation in the residuals an important condition for model appropriateness the Ljung-Box Q-test (Box and Jenkins, 1976) was executed across a variety of lag orders were assigned as follows:

$$Q = n(n+2) \sum_{k=0}^{h} \frac{\rho k^2}{n-k}$$

These diagnostic checks ensured model adequacy and reliability for forecasting.

Evaluation of model strength and precision

A comprehensive evaluation of ARIMA model specifications was applied to evaluate the empirical forecasting strength and parameter efficiency employing a suite of penalized likelihood criteria including the Akaike Information Criterion, AIC = 2k–2logL given by Akaike 1974, its sample-size adjusted variant the Corrected Akaike Information Criterion, *2k(k+1)/n-k-1*, introduced by Hurvich, 1989 and Bayesian Information Criterion, BIC = k log (n) - 2logL, established by Schwarz, 1978. For overall accuracy testing following criteria were assessed. Mean Absolute Error (MAE) were evaluated to deviation of predictions value (y_i) from the actual values (x_i) introduced by MAE = $1/n\Sigma^{n}_{i=1}|yi-xi|$ given by Willmott and Matsuura (2005). Root Mean Square Error (RMSE) were use to detect large errors count employing squares of the errors before averaging formulated by Willmott and Matsuura (2005) as follows:

$$RMSE = \sqrt{\{\frac{1}{n} \sum_{i=1}^{n} (y_i - x_i)\}^2}$$

For express as percentage Mean Absolute Percentage Error (MAPE) introduced by Hyndman and Koehler (2006) were calculated using the average of absolute percentage errors between forecasted (y_i) and actual (x_i) values, typically multiplied by 100 stated as follows:

$$MAPE = 100 \times \frac{1}{n} \sum_{t=1}^{n} |\frac{x_i - y_i}{x_i}|$$

Finally, Mean Absolute Scaled Error (MASE) were assessed for non-seasonality applying the formula given by Hyndman and Koehler (2006) expressed as follows:

$$MASE = \frac{\frac{1}{n}\sum_{t=1}^{n} |e_t|}{\frac{1}{T-1}\sum_{t=2}^{T} |Y_t - Y_{t-1}|}$$

where, $e_t = Y_t - \tilde{Y}_t$ is the forecast error, n = number of forecasts, T = length of training sample, denominator

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= MAE of naive forecast (previous value).

These criteria offer a robust framework for model selection by systematically evaluating the tension between overfitting and underfitting model, where lowest value considered as optimum model.

Data collection and statistical analysis

Yearly datasets related to rapeseed mustard harvested area (hectares), production (tons), consumption (tons) and imports (tons) for six decades (1964-2024) were retrieved from Index Mundi (https://www.indexmundi.com/agriculture), which assembles and reports national agricultural statistics from the United States Department of Agriculture (USDA, 2025) and other recognized institutions. The data were ratified using cross-authentication techniques employing supplementary data sources like FAOSTAT (FAO, 2025) and the Bangladesh Bureau of Statistics (BBS, 2025) to preserve precision and internal consistency. All data points were examined for intra-dataset consistency. Subsequently data were structured for chronological evaluation with no imposed interruptions to uphold data validity of observed trends. Statistical analysis was accomplished utilizing Rstudio version R.4.3.2 (R Core Team, 2021).

Results

ARIMA model for rapeseed harvested area

The raw dataset of rapeseed mustard harvested area was primarily visualized employing graphical illustrations (Figure 1), revealed a steady rise over time, advocating possible non-stationarity in the data series. The stationarity test was applied to ensure that the time series exhibited constant statistical properties over time. A stationary process is characterized by time-invariant mean, variance, and autocorrelation, which are essential assumptions for reliable ARIMA modeling and accurate forecasting. The stationary test was investigated using ADF test and the KPSS test at valid level of significance. The ADF test was accepted the null hypothesis ($p > 0.05$) of non-stationarity, indicating the presence of a unit root, underscoring that the data was non-stationary. Similarly, the KPSS test rejected the null hypothesis of stationarity ($p < 0.05$), recommending a non-stationary data set (Table 1).

accuracy testing, with the minimum values observed across BIC (-80.58), AIC (-86.86) and AICc (-86.66) (Table 2).

Successively, rigorous diagnostics were evaluated to ensure that the model specification was suitable. The Jarque-Bera normality test was performed on the residuals of the fitted models, and the result was a p-value of 0.00000022 < 0.01 (Table 3), recommending that the residuals were not normally distributed. The histogram is positively skewed, with a concentration of residuals between −0.05 and 0.15 (Figure 4a), indicating a deviation from normality. The absence of autocorrelation, underscoring the model correctly captures the temporal dynamics of the rapeseed mustard production area data series, notwithstanding the possibility of some interpretation inefficiencies brought on by the inadequacy of normality. If the timeseries is homoscedastic and serially uncorrelated, non-

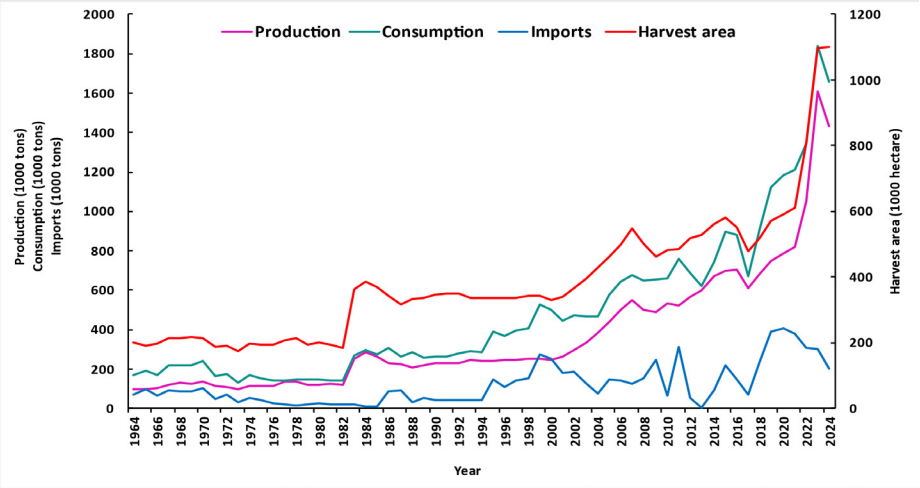


Figure 1: *Rapeseed-mustard production, consumption, imports (1000 tons), and harvest area (1000 hectares) in Bangladesh from 1964 to 2024, highlighting growing consumption, fluctuating imports, and a gradual rise in production and harvested area.*

Table 1: *Evaluation of structural stability of rapeseed mustard production area (hectare), production (ton), consumption (ton) and imports (ton).*

Stationarity Test	Data type	ADF statistics			KPSS-statistics		
		D.F.	P-value	Result	Level	P-value	Result
Rapeseed harvested area	level	-1.23	0.88	Non-stationary	1.37	0.01	Non-stationary
	log-transformed	-2.88	0.22	Non-stationary	1.50	0.01	Non-stationary
	1st difference	-4.40	0.01	Stationary	0.16	0.10	Stationary
Rapeseed production	level	0.77	0.99	Non-stationary	1.32	0.01	Non-stationary
	log-transformed	-2.72	0.27	Non-stationary	1.56	0.01	Non-stationary
	1st Difference	-4.74	0.01	Stationary	0.13	0.1	Stationary
Rapeseed consumption	level	2.46	0.99	Non-stationary	1.33	0.01	Non-stationary
	log-transformed	-2.55	0.34	Non-stationary	1.54	0.02	Non-stationary
	1st difference	-4.34	0.01	Stationary	0.17	0.15	Stationary
Rapeseed imports	level	-2.80	0.24	Non-stationary	0.96	0.03	Non-stationary
	log-transformed	-2.59	0.34	Non-stationary	0.75	0.02	Non-stationary
	1st difference	-4.96	0.01	Stationary	0.06	0.3	Stationary

Note: D.F. = Dickey-fuller

Table 2: *The established ARIMA (p, 1, q) model designs, along with their employed AIC, AICc, and BIC values, to determine the optimum model for forecasting the area, production, consumption, and imports of rapeseed mustard.*

ARIMA models	Rapeseed harvested area			Rapeseed production			Rapeseed consumption			Rapeseed imports		
ARIMA (p, d, q)	AIC	AICc	BIC	AIC	AICc	BIC	AIC	AICc	BIC	AIC	AICc	BIC
ARIMA (0,1,1)	-86.00	-85.93	-81.81	-61.50	-61.43	-57.31	-44.84	-44.84	-42.73	145.51	145.58	149.70
ARIMA (0,1,0)	-85.98	-85.98	-83.89	-61.23	-61.23	-59.14	-44.14	-44.07	-39.91	152.99	152.99	155.09
ARIMA (1,1,0)	-85.72	-85.65	-81.53	-61.26	-61.19	-57.07	-44.17	-44.10	-39.95	151.89	151.96	156.08
ARIMA (0,1,2)	-84.31	-84.10	-78.03	-59.58	-59.37	-53.30	-42.18	-41.97	-35.84	142.85	143.05	149.13
ARIMA (1,1,1)	-86.86	-86.66	-80.58	-59.57	-59.36	-53.29	-42.17	-41.97	-35.84	145.49	145.69	151.77
ARIMA (2,1,0)	-84.17	-83.96	-77.89	-59.56	-59.35	-53.28	-42.17	-41.97	-35.84	141.56	141.77	147.85
ARIMA (1,1,2)	-85.26	-84.84	-76.89	-57.60	-57.18	-49.23	-42.42	-42.00	-33.97	143.02	143.44	151.39
ARIMA (0,1,3)	-82.34	-81.92	-73.96	-57.59	-57.16	-49.21	-40.34	-39.93	-40.34	142.96	143.38	151.34
ARIMA (2,1,1)	-85.26	-84.84	-76.89	-57.58	-57.16	-49.21	-40.17	-39.76	-31.73	143.34	143.76	151.72
ARIMA (3,1,0)	-82.17	-73.79	-82.17	-57.57	-57.14	-49.19	-40.17	-39.76	-31.73	143.42	143.84	151.80
ARIMA (1,1,3)	-83.27	-82.56	-72.80	-55.60	-54.88	-45.13	-38.79	-38.09	-28.23	144.83	145.55	155.31
ARIMA (2,1,2)	-83.97	-83.25	-73.49	-55.60	-54.88	-45.13	-44.38	-43.68	-33.83	144.81	145.53	155.28
ARIMA (3,1,1)	-83.27	-82.56	-72.80	-55.58	-54.86	-45.11	-40.41	-39.71	-29.86	144.09	144.81	154.56
ARIMA (3,1,3)	-81.73	-80.17	-67.07	-55.36	-53.77	-40.70	-42.68	-41.15	-27.90	148.02	149.57	162.68
ARIMA (3,1,2)	-81.39	-80.30	-68.82	-53.61	-52.50	-41.04	-41.39	-28.73	-41.39	146.09	147.18	158.66
ARIMA (2,1,3)	-81.31	-68.75	-81.31	-53.60	-52.49	-41.04	-41.30	-40.2	-28.63	146.80	147.89	159.36

normal residuals do not always make predictions less reliable. However, The Ljung-Box test was utilized to calculate the homoscedasticity and independence of the residuals and the finding ($p = 0.96 > 0.05$), provided non-significant autocorrelation exposing the residuals were uncorrelated, indicating the validity of the model. The model also unveiled the lowest values for MAE (0.06), MASE (0.97), MAPE (1.06), and (RMSE (0.11) (Table 4). The ARIMA (1,1,1) model displayed its superiority fulfilling all criteria.

ARIMA model for rapeseed mustard production

The visual inspection of the rapeseed-mustard time series revealed a pronounced upward trend, indicating non-stationarity in the raw data (Figure 1). To formally assess this, ADF and KPSS tests were

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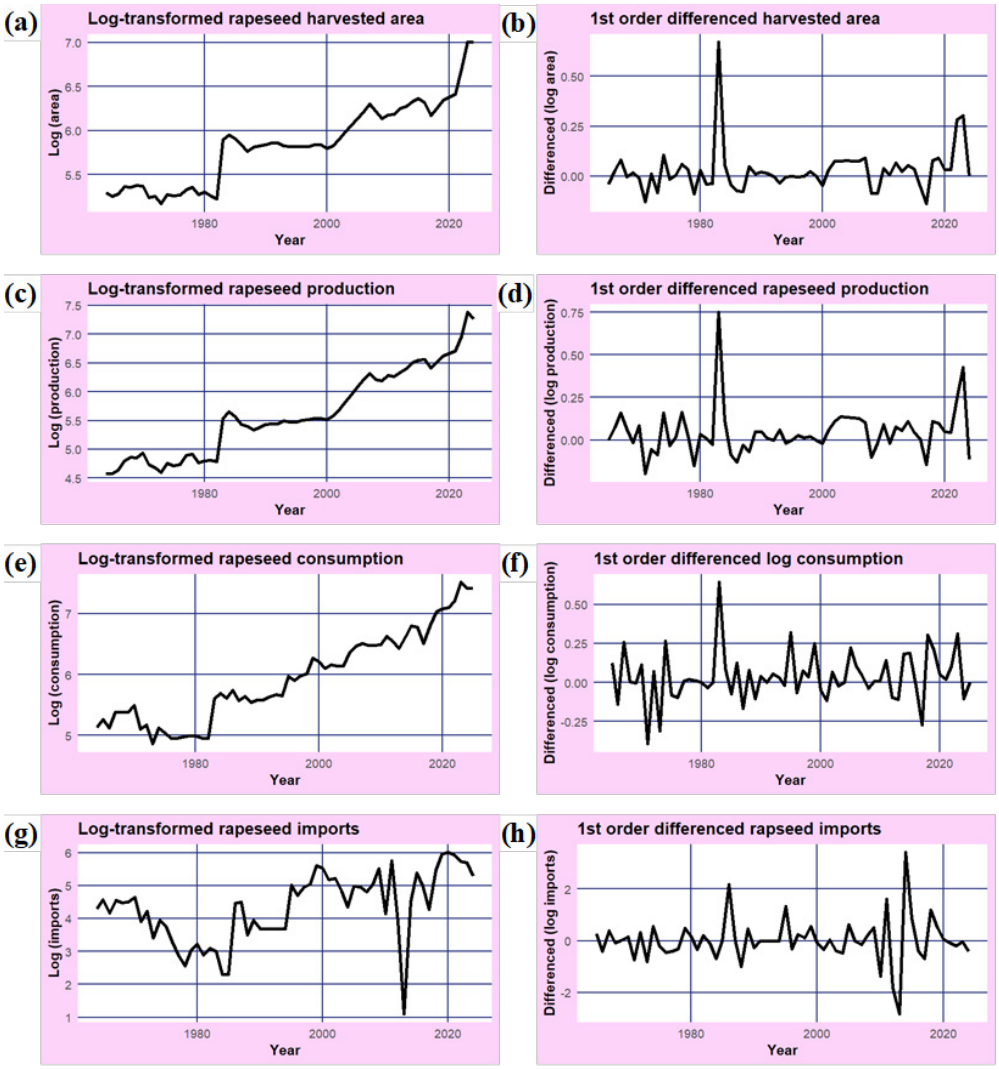


Figure 2: *Log-transformed and first-order differenced time series of rapeseed-mustard harvested area, production, consumption, and imports in Bangladesh (1964-2024), illustrating variance stabilization and stationarity diagnostics for time series forecasting.*

Table 3: *Residual analysis with the jarque-bera test and the ljung-box test*

Check residuals (auto-model) Jarque-Bera test and Ljung-Box test					
Test names	Parameters	Rapeseed area	Rapeseed production	Rapeseed consumption	Rapeseed imports
Jarque-Bera test	X-squared	603.19	421.29	24.41	23.65
	p-value	0.00000022	0.00000023	0.000000498	0.000000731
Ljung-Box test	Q*	3.48	5.8	10.43	3.28
	p-value	0.96	0.75	0.40	0.97

conducted, both confirming the presence of a unit root and non-stationarity (Table 1). After that data were log-transformed to alleviate non-stationarity but still revealed non-stationarity in both the ADF and KPSS tests. Consequently, first-order differencing was performed. After differencing, the ADF test rejected the null hypothesis of non-stationarity ($p = 0.01 < 0.05$), while the KPSS test failed to reject the null hypothesis of stationarity ($p = 0.10 > 0.05$), confirming stationarity. This indicates that the series is integrated of order one, I(1), a common feature of economic and agricultural time series.

After that the selection of the differencing order, the Autocorrelation (ACF) and Partial Autocorrelation (PACF) plots of the differenced series were analyzed to determine acceptable p and q values. In the Figure 3g, there was a clear truncation in the ACF after the

first lag, indicating a possible MA (1) process, while the PACF with no lag, indicated a lack of meaningful autocorrelations in the series (Figure 3h). So ARIMA (0,1,1) is the most probable candidate for the model selection according to the visual observation. However, a systematic approach involving multiple candidate ARIMA models was employed following initial visual diagnostics to minimize subjective bias and ensure a comprehensive model evaluation. Accordingly, many alternative ARIMA models were formed and assessed using the BIC, AIC and corrected AIC. The ARIMA (0,1,1) model surpassed all possible candidate, with the lowest AIC (- 61.50), AICc (-61.43), and BIC (-57.31) values (Table 2). The suitability of the selected ARIMA (0,1,1) model was carefully evaluated using different residual diagnostics test. The Jarque-Bera test rejected the null hypothesis of normality ($p = 0.00000023 < 0.01$), advocating that the residuals were not normally distributed (Table 3). Additionally, histogram was employed for graphical illustration, where the residuals distribution displayed a little deviation from normality with a slight positive skew and a bell-shaped distribution around zero (Figure 4b). The absence of autocorrelation, signifying the model correctly captures the temporal dynamics of the rapeseed mustard production series, despite the possibility of some interpretation inefficiencies brought on by the lack of normality. If the time series is homoscedastic and serially uncorrelated, non-normal residuals do not always generate predictions less reliable. Further, the homoscedasticity and independence of the residuals were evaluated using the Ljung-Box test; the results ($p = 0.75 > 0.05$) presented non-significant autocorrelation, suggesting that the residuals were uncorrelated and confirming the model's validity. The better ARIMA (0,1,1) model could provide a precise prediction. The model also unveiled the lowest values for MAE (0.06), MASE (0.97), MAPE (1.06), and RMSE (0.11) (Table 4). The ARIMA (0,1,1) model established its superiority fulfilling all criteria.

ARIMA model for rapeseed mustard consumption

The raw dataset on rapeseed mustard consumption, which was mostly represented by graphical representations (Figure 1), displayed a consistent

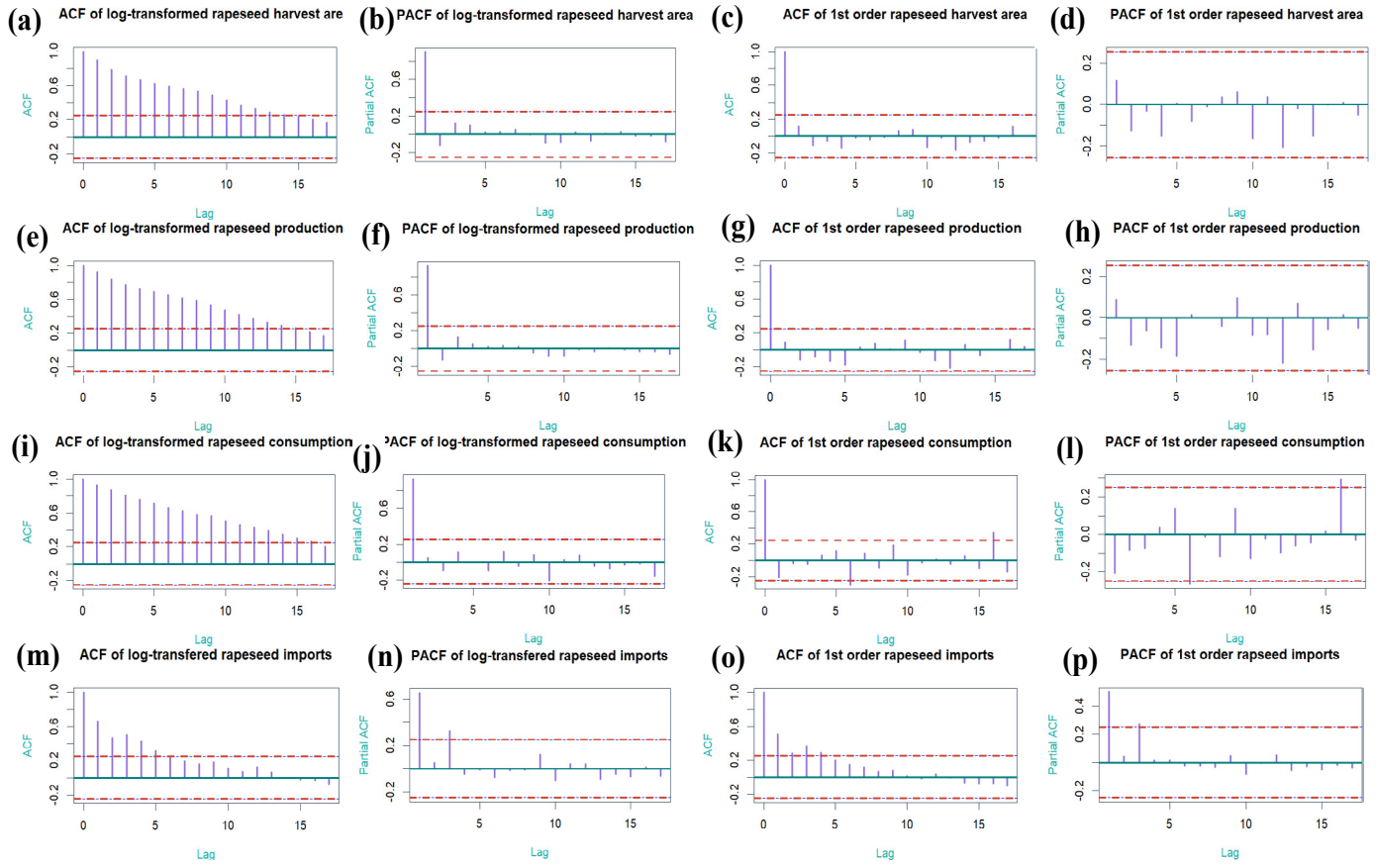


Figure 3: *Autocorrelation (ACF) and partial autocorrelation (PACF) diagnostics of log-transformed and first-order differenced series for rapeseed-mustard harvested area, production, consumption, and imports in Bangladesh (1964–2024). The plots reveal strong autocorrelation structures in the original series and demonstrate stationarity post-differencing, thereby validating the use of ARIMA modeling for robust time series forecasting.*

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increase over time, suggesting that the data series may not be stationary. Stationarity, defined by constant mean, variance, and autocorrelation over time, is essential for reliable time-series forecasting. To assess this property, both ADF and KPSS tests were conducted at a 5% significance level. The ADF test failed to reject the null hypothesis of a unit root ($p = 0.99 > 0.05$), while the KPSS test rejected the null hypothesis of stationarity ($p = 0.01 < 0.05$), confirming that the original series was non-stationary (Table 1). In addition, the original data series were converted to natural log-transformed to lessen heteroscedasticity and stabilize the variance (Figure 2c). The log-transformed data were rechecked to observe the existence unit root. Both the ADF ($p = 0.27 > 0.05$) and KPSS ($p = 0.01 < 0.05$) tests uncovered unit root, indicating non-stationary at the 5% level of significance. Likewise, first-order differencing was functioned for the stationary test, where both ADF ($p = 0.01 < 0.05$) and KPSS ($p = 0.1 > 0.05$) tests delivered stationary results at the 5% level of significance (Table 1.), indicating the value of differencing order d = 1. Following this, the ACF and PACF plots of the differenced series were analyzed to identify suitable autoregressive (AR) and moving average (MA) components. In the Figure 3k, there was a strong truncation in the ACF after the first lag, indicating a possible MA (1) process. Similarly, the PACF exhibited a sharp spike in the first lag, suggesting a possible AR (1) procedure (Figure 3l). So, according to visualization ARIMA (1,1,1) is a significant candidate for superior model. Although, a standard visual technique was applied for initial diagnoses, a systematic method using several candidate ARIMA models was essential to evade subjective bias and bolster an inclusive estimation. Accordingly, multiple candidate ARIMA models were formed to detect the best model (Table 2). Among the feasible models, the ARIMA (0,1,1) model surpassed all contending models of accuracy testing, exhibiting the smallest values across BIC (- 42.73), AIC = (-44.84) and AICc (- 44.84) (Table 2). Consecutively, rigorous diagnostics tests were reviewed to validate the accuracy of the model specification. The Jarque-Bera normality test was performed on the fitted model's residuals, and the result presented a p-value of $0.000000498 < 0.01$ (Table 3), inferring that the residuals were not normally distributed. Then, for graphical illustration histogram were utilized where histogram showed roughly bell-shaped distribution and majority of the residuals are centered around zero with limited outliers, underscoring approximately normal distribution (Figure 4c). Despite the possibility of some interpretation inefficiencies brought on by the lack of normality, the distribution still has likelihood to be fit model if the time series is homoscedastic and serially uncorrelated, as non-normal residuals do not always make predictions less reliable. However, The Ljung-Box test was applied to estimate the homoscedasticity and independence of the residuals and the result ($p = 0.40 > 0.05$), offered non-significant autocorrelation displaying the residuals were uncorrelated, suggesting the validity of the model. The model also exposed the lowest values for MAE (0.11), MASE (0.96), MAPE (1.87), and RMSE (0.15) (Table 4). The ARIMA (0,1,1) model demonstrated its superiority for rapeseed mustard fulfilling all criteria.

Table 4: *Model selection criteria and forecast accuracy measures for the ideal ARIMA model.*

Accuracy test	Rapeseed harvested area	Rapeseed production	Rapeseed consumption	Rapeseed imports
RMSE	0.11	0.13	0.15	0.73
MAE	0.06	0.08	0.11	0.50
MAPE	1.06	1.49	1.87	14.87
MASE	0.97	0.94	0.96	0.95
Selected model	ARIMA (1,1,1)	ARIMA (0,1,1)	ARIMA (0,1,1)	ARIMA (2,1,0)

The raw dataset of rapeseed mustard imports was primarily observed utilizing graphical illustrations (Figure 1), uncovered a progressive escalation over time, pointing toward a likelihood of non-stationarity in the data series. Stationary is essential for accurate modeling and forecasting that's why the stationary test was investigated using ADF test and the KPSS test at valid level of significance. The ADF test accepted the null hypothesis ($p = 0.24 > 0.05$) of non-stationarity, demonstrating the presence of a unit root and confirming that the data was non-stationary. The KPSS test similarly rejected the null hypothesis of stationarity ($p = 0.03 < 0.05$), indicating a non-stationary data collection (Table 1). To, eradicate the non-stationary, the data were transformed using a logarithmic scale to the original series to decrease heteroscedasticity and stabilize the variance (Figure 2g) and checked again to observe the existence of unit root, where both the ADF ($p = 0.34 > 0.05$) and KPSS ($p = 0.02 < 0.05$) tests exposed unit root, implying non-

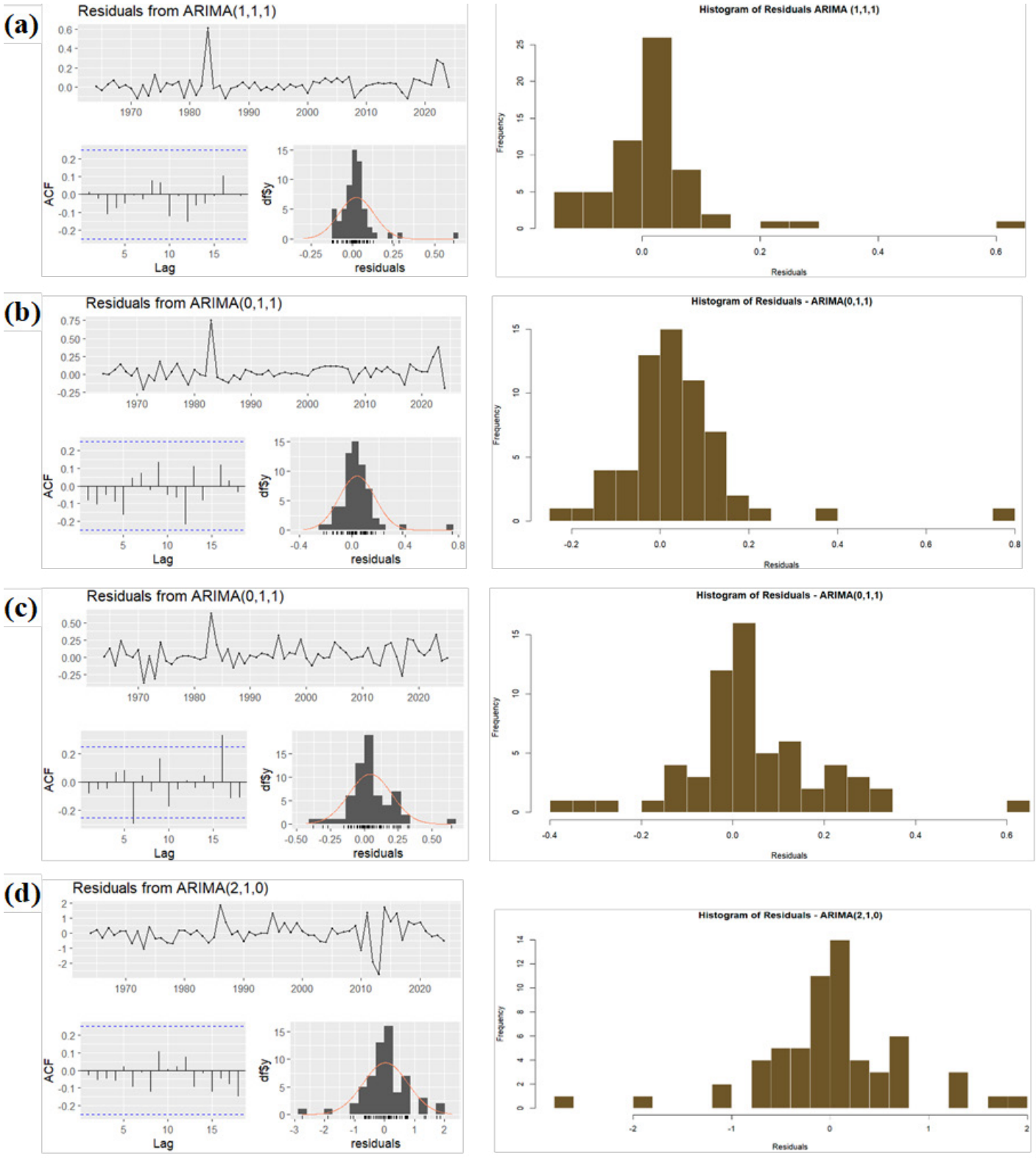


Figure 4: *Diagnostic plots of residuals from different ARIMA models: (a) ARIMA (1,1,1), (b) ARIMA (0,1,1), (c) ARIMA (0,1,1), and (d) ARIMA (2,1,0). Each panel displays the residual time series (top), autocorrelation function (ACF) plot (bottom left), normal Q-Q plot with density fit (bottom center), and histogram of residuals (right).*

stationary at the 5% level of significance (Table 1).

After that, the first-order differencing was conducted for the stationary test (Figure 2h), where both ADF (p = 0.01< 0.05) and KPSS (p = 0.3 > 0.05) tests produced stationary results at the 5% level of significance (Table 1), determining differencing order d = 1. Following the determination of the differencing order (d = 1), the optimal autoregressive and moving average parameters (p and q) were determined

applying the data visualization strategies such as ACF and PACF for the first differenced series. ACF divulged a sharp spike at lag 2 (Figure 3o), denoting a potential MA (2) procedure, while PACF displayed a significant spike at lag 1 (Figure 3p), indicating an AR (1) process. According to the observation, ARIMA (2,1,1) is a best candidate for the fit model. Then, a systematic procedure via several candidate ARIMA models was essential to avoid subjective bias and confirm a comprehensive assessment. From the numerous evaluated models, the ARIMA (2,1,0) model demonstrated superior performance over all competing models of accuracy testing, with the lowest values across BIC (147.85), AIC (141.56) and AICc (141.77) (Table 2).

ARIMA model for rapeseed mustard imports

Consecutively, rigorous diagnostics were assessed to ensure that the model specification was suitable. The Jarque-Bera normality test was performed on the fitted model's residuals, and the result was a p-value of 0.000000731< 0.01 (Table 3), suggesting that the residuals were not normally distributed. The more precise test visual graphical illustrations were employed, where the majority of the residuals are situated between -0.5 and 0.5, approximately centered around zero, with a minor positive skewness indicating that the model well fits most of the data (Figure 4d). Additionally, for more conformation the Ljung-Box test was used, whereas the finding ($p = 0.97 > 0.05$), demonstrated non-significant autocorrelation revealing the residuals were uncorrelated, indicating the validity of the model (Table 3).

Finally, after validity test model accuracy test were performed, where the model exposed the lowest values for MAE (0.50), MASE (0.95), MAPE (14.87), and RMSE (0.73) (Table 4). The ARIMA (1,1,1) model demonstrated its superiority fulfilling all criteria. According to model fit test and accuracy test, ARIMA (2,1,0) is the best model for the rapeseed imports production.

Prediction value of the rapeseed models

The ARIMA-based predictions for four important metrics of rapeseed mustard harvested area, production, consumption and imports in Bangladesh demonstrated a statistically reliable and economically significant increasing trend. The rapeseed production area, production, consumption and imports for 2025-2039, presented in Figure 5 and Table 5, varies considerably from historical patterns. The growth of rapeseed area followed a moderate upward trend from 1964 to 2024 (Figure 5a).

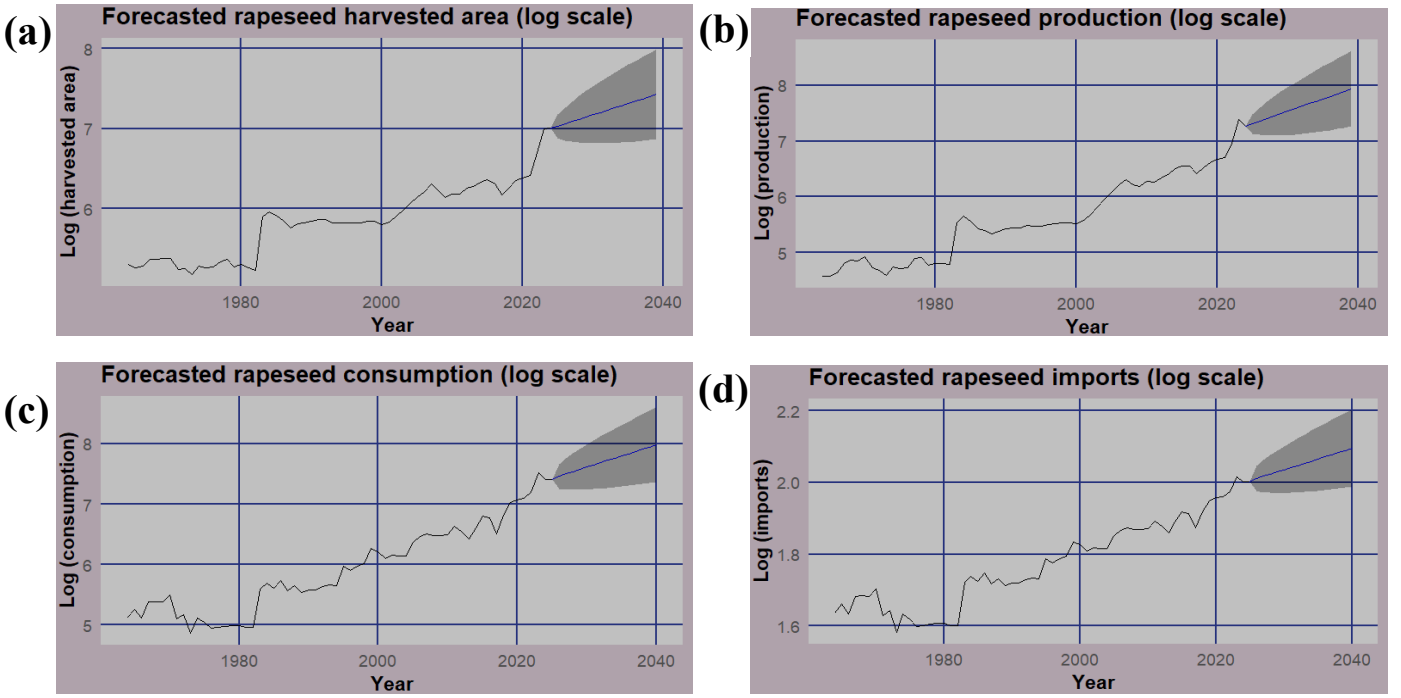


Figure 5: *This figure illustrates a comprehensive time series study of rapeseed-mustard production trends in Bangladesh, integrating historical data with ARIMA-based projections for 2025-2039. Panels (a), (b), (c), and (d) provide log-transformed forecasts for rapeseed mustard production area (hectare), production (ton), consumption (ton), and imports (ton), with a focus on fundamental trends and development patterns.*

Links Researchers

Table 5: *Projected rapeseed mustard production area, production, consumption, and imports are illustrated using time series forecasting.*

Years	Rapeseed harvested area			Rapeseed production			Rapeseed consumption			Rapeseed imports		
	F.V. (1000)	LCL (1000)	UCL (1000)	F.V. (1000)	LCL (1000)	UCL (1000)	F.V. (1000)	LCL (1000)	UCL (1000)	F.V. (1000)	LCL (1000)	UCL (1000)
2025	1131.70	905.70	1414.0	1495.58	1143.89	1955.41	1745.47	1277.89	2384.13	230.29	52.04	1019.01
2026	1164.32	849.67	1595.48	1564.18	1070.61	2285.28	1811.87	1224.17	2681.70	261.54	43.30	1579.58
2027	1197.87	814.40	1761.89	1635.92	1028.26	2602.68	1880.80	1189.07	2974.93	236.48	36.26	1542.20
2028	1232.40	789.32	1924.16	1710.96	1000.88	2924.79	1952.36	1164.80	3272.37	231.37	29.06	1841.68
2029	1267.91	770.47	2086.51	1789.43	982.60	3258.78	2026.63	1147.75	3578.46	243.19	24.55	2408.94
2030	1304.46	755.87	2251.17	1871.51	970.52	3608.94	2103.72	1135.92	3896.05	241.57	21.31	2737.57
2031	1342.04	744.39	2419.55	1957.35	963.01	3978.37	2183.75	1128.09	4227.28	237.01	18.29	3069.85
2032	1380.72	735.30	2592.67	2047.12	959.04	4369.69	2266.82	1123.43	4573.92	239.14	15.90	3595.80
2033	1420.52	728.12	2771.31	2141.01	957.94	4785.22	2353.05	1121.38	4937.52	240.40	14.01	4124.63
2034	1461.46	722.51	2956.14	2239.21	959.22	5227.23	2442.57	1121.55	5319.55	239.08	12.35	4626.86
2035	1503.58	718.21	3147.73	2341.92	962.55	5697.94	2535.49	1123.62	5721.42	238.97	10.94	5219.73
2036	1546.91	715.03	3346.60	2449.33	967.68	6199.61	2631.95	1127.37	6144.53	239.56	9.75	5882.63
2037	1591.49	712.82	3553.27	2561.68	974.40	6734.56	2732.07	1132.61	6590.26	239.42	8.72	6566.79
2038	1637.35	711.46	3768.21	2679.17	982.58	7305.19	2836.00	1139.21	7060.06	239.22	7.83	7305.85
2039	1684.54	710.86	3991.91	2802.05	992.10	7914.03	2943.89	1147.06	7555.38	239.34	7.05	8119.11
CAGR%	2.88%			4.59%			3.80%			0.28%		

However, from year 2025 onward, the forecasts indicate an accelerated growth from 1131.70 thousand hectares in year 2025 to 1684.54 thousand hectares in 2039, with an 2.88% compound annual growth rate (CAGR), which may be accelerated by rapidly growing consumer demand as consumption of rapeseed increased highly (Table 5). The current forecast model predicts that rapeseed consumption will rise to 2,943.89 thousand tons by 2039, compare to 1745.47 thousand tons in year 2025, manifesting a compound annual growth rate (CAGR) of 3.80%. The production area and consumption are expanding, resulting in a notable increase in rapeseed production, which is growing at a compound annual growth rate of 4.59%. Current production is 1,495.58 thousand tons, predicted to reach 2,802.05 thousand tons by 2039. Although, the historical and predicted data on rapeseed production manifested a noticeable and consistent increase, the rapeseed mustard sector of Bangladesh still dependent on imports. The ARIMA model specified that rapeseed imports would increase significantly from 230.29 thousand tons in 2025 to 239.34 thousand tons in 2039.

Discussion

Projecting rapeseed mustard trends using rigorous statistical modelling is essential for attaining food and nutritional security in Bangladesh, where more than 90% of domestic edible oil demand is dependent on imports (USDA, 2025). This investigation presents a data-driven, time series forecasting framework employing the ARIMA model, which achieved the best accuracy performance and residual diagnostics compared to other statistical models (Shadab *et al.*, 2019; Alsheheri, 2025). The results demonstrate significant expansion in domestic production and cultivated land, a slight increase in consumption, and a stability in imports from 2025 to 2039, pointing to a core transformation in the oilseed economy of the country.

The forecasting in agriculture is frequently deter by sporadic oscillations, insufficient data, and fundamental time-dependent non-stationary data. The ARIMA model, a reliable method initiated by Box and Jenkins (1976), delivers steadfast stability and reliability regarding BIC, AIC, MAPE, and RMSE accuracy tests. Residual diagnostics endorsed the assumptions of normality, independence, and insufficiency of autocorrelation, thus validating model fitness. The notable accuracy and fitness of simpler ARIMA models explicitly ARIMA (1,1,1) for area, ARIMA (0,1,1) for production, ARIMA (0,1,1) for consumption, and ARIMA (2,1,0) for imports is consistent with global studies in agricultural

forecasting (Shadab *et al*., 2019; Jannat *et al*., 2022; Begum *et al*., 2024).

These findings expose a favorable compound annual growth rate (CAGR) of 4.59% for rapeseed-mustard production and 2.88% in harvested area a manifestation of productivity gains seemingly triggered by innovation-driven agronomic practices, high-yielding varieties, and strategic policy intervention. Conversely, imports indicate limited progress (CAGR: 0.28%), whereas consumption demonstrates a persistent upward trajectory (CAGR: 3.80%), suggesting a diminishing imports but sustained gap between demand and supply. This pattern poses a threat to the ongoing reliance on imports within Bangladesh's oil crop sector, which presently satisfies over 90% of domestic supply through imports particularly from Indonesia, Malaysia, and Argentina (Barois *et al*., 2024; USDA, 2025). This moderation in the growth trajectory of imports deviates strongly from previous patterns revealing a blend of endogenous improvements and exogenous constraints. The excessive dependence on imported edible oils significantly endangers the rapeseed industry in Bangladesh, especially during global crises such as supply chain breakdowns, geopolitical conflicts, or price volatility (Mila *et al*., 2019; Begum *et al*., 2024). Under these circumstances, import costs escalate swiftly and destabilize the local economy. This reliance on external sources restricts local production, discourages investment, and distracts policymakers, leaving an underperforming rapeseed sector and unresponsive to shortages threatening food and nutritional security. Recent global disruptions, such the COVID-19 pandemic and geopolitical instability, have highlighted the fragility of relying on foreign commodity supplies (Ben Hassen and El Bilali, 2022; Urak *et al*., 2024).

Unlike Bangladesh, which demonstrates positive advancements in the oilseed sector, neighboring India faces stagnant oilseed production and an increasing reliance on imported edible oils. This is primarily influenced by dietary shifts towards oil-rich foods, increasing input prices, fragmented landholdings, and inadequate post-harvest infrastructure volatility (Mila *et al*., 2022). Even though India is one of the top suppliers of oilseeds in domestic and international market, more than 60% of its edible oil needs are imported, leaving it susceptible to fluctuations in global prices and supply interruptions (Delvadiya *et al*., 2023; Monshi *et al*., 2026b). On the other hand, the implementation of integrated policy measures like the National Edible Oilseed Expansion Program (NEOEP) and the anticipatory institutional responses incorporated in the 8th five-year plan appear to have reinforced the nation's sectoral resilience (Iqbal *et al*., 2022; Sharma *et al*., 2024). These programs strive to ensure farmer profitability under minimum price assurance frameworks, subsidized inputs, and agro-marketing facilitation platforms, together with expanding production through breeding programs focused on varietal enhancement and extension services (Hossain *et al*., 2024; Mouri *et al*., 2026b). The emphasis on integrated value chains that combine upstream production with midstream post-harvest processing and downstream market access has improved Bangladesh's competitiveness. Investment in decentralized oil extraction units, cold chain logistics, and rural agro-processing facilities has begun to yield positive results, particularly in the rapeseed and mustard production areas of Rajshahi, Rangpur, and Barisal divisions (Mila *et al*., 2019; Mila *et al*., 2022; Begum *et al*., 2024). If these approaches are expanded and institutionalized, they could not only diminish the edible oil import expenditure but also convert Bangladesh into a net contributor to regional oilseed security.

The findings of the projection deliver an appropriate framework for policy and investment, strengthening the agricultural sector. Given that production exceeds imports yet remains insufficient for consumption, Bangladesh must adopt two strategies: augmenting domestic crushing capacity and securing value retention within national supply chains. This corresponds with Sustainable Development Goals (SDG 2: Zero Hunger and SDG 12: Responsible Consumption and Production), in addition to Bangladesh's Nationally Determined Contribution targets under the Paris Agreement (Atukunda *et al*., 2021; Tabassum *et al*., 2023; Barois *et al*., 2024; Fan *et al*., 2024). To convert predictive models into policy interventions, scientifically validated policy tools such as state-mandated floor price, subsidized input distribution schemes, and contract farming arrangements must be synchronized with anticipated demand expansion. Additionally, the establishment of regional oilseed clusters, facilitated by transport logistics, cold chains, and market access, can close the yield-market gap and foster inclusive growth (Mila *et al*., 2019; Begum *et al*., 2024).

The ARIMA models discussed exhibit strong prediction capabilities under present data conditions, nevertheless, their univariate framework and linear assumptions constrain their responsiveness to external shocks. Subsequent investigations may integrate meteorological variability, fertilizer costs, global edible oil benchmarks, and policy indicators utilizing ARIMAX or hybrid models (Iqbal *et al*., 2022; Delvadiya *et al*., 2023; Sharma *et al*., 2024). Bayesian structural time series, spatial econometrics, and deep learning methodologies, viz. LSTM networks, present exciting opportunities for elucidating intricate, dynamic connections across temporal and spatial dimensions (Alsheheri *et al*., 2025). The growing accessibility of satellite-based agricultural surveillance and open-source climatic data may facilitate near real-time forecasting and adaptive policy formulation. In vulnerable economies such as Bangladesh, where agricultural planning must contend with significant climatic risks and trade vulnerability, such foresight tools are essential strategic necessities rather than simply technical luxury.

Conclusions and Recommendations

This study developed ARIMA-based forecasting models for rapeseed-mustard harvested area, production, consumption, and imports in Bangladesh. The best-performing models were ARIMA (1,1,1) for harvested area, ARIMA (0,1,1) for production, ARIMA (0,1,1) for consumption, and ARIMA (2,1,0) for imports, selected based on AIC, AICc, and BIC criteria and validated through diagnostic tests including the Jarque-Bera and Ljung-Box statistics. The forecasting results indicate a gradual increase in harvested area and domestic production, suggesting slow progress toward self-sufficiency. Consumption is projected to rise steadily, while import levels remain relatively stable, indicating a persistent supply-demand gap in the oilseed sector. Based on these findings, targeted policy measures are required to accelerate productivity growth through the adoption of high-yielding and climate-resilient varieties and improved agronomic practices. The continued reliance on imports despite increasing production underscores the need to strengthen domestic supply chains and reduce import dependency. Furthermore, the demonstrated reliability of ARIMA models suggests that integrating time-series forecasting into national agricultural planning can support evidence-based decision-making, efficient resource allocation, and long-term food security strategies in Bangladesh.

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Novelty Statement

The present study is the first to apply a comprehensive ARIMA-based time series analysis over an extensive historical dataset (1964-2024) to forecast Bangladesh's rapeseed-mustard production, consumption, and imports up to 2039. The integration of rigorous statistical validation with targeted policy recommendations offers a novel, evidence-based framework for enhancing domestic edible oil self-sufficiency under climatic and market uncertainties.

Authors' Contributions

Mahadi Hasan Monshi: Conceptualization, Investigation, Methodology, Project administration, Software, Data curation, Formal analysis, Resources, Visualization, Writing- original draft.
Muntarina Hussan Mouri: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Writing- original draft.
Rehenuma Tabassum: Supervision, Formal analysis, Methodology, Conceptualization, Data curation, Visualization, Writing- original draft, review & editing.
Jahidul Hassan: Resources, Validation, Writing- review & editing.
Md. Shakhawat Hossain: Resources, Validation, Writing- review & editing.
Md. Sarowar Alam: Resources, Validation, Writing- review & editing.
Ahmed Khairul Hasan: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Writing- original draft, Fund Acquisition.
Fakhrul Islam Monshi: Fund acquisition, Conceptualization, Supervision, Investigation, Methodology, Project administration, Funding acquisition, Resources, Validation, Writing- original draft, Writing- review, editing, and finalizing the manuscript.

Generative AI and AI-assisted technology statement
The authors declare that no generative AI and AI

assisted technology was used in the creation of this manuscript.

Conflict of interest

The authors declared that they have no conflict of interest.

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