

Forecasting Rice Production in Bangladesh: A Comparative Analysis of Conventional and Hybrid Time Series Approach

Md. Sourove Akther Momin, Md. Rabiul Hasan and Salaha Uddin Chowdhury Shaju

Department of Statistics and Data Science

Jahangirnagar University

Dhaka, Bangladesh

Sur.sor269@gmail.com

Abstract

This study presents a comprehensive evaluation of conventional and hybrid forecasting models for predicting seasonal rice production in Bangladesh, analyzing data from 1970 to 2023 across three major growing seasons: Aus, Amon, and Boro. The research implements sixteen distinct forecasting models, combining traditional approaches with innovative hybrid methodologies to enhance prediction accuracy. The conventional models include ARIMA, ETS, ANN, and TBATS, while the hybrid models merge these traditional approaches with advanced techniques such as WARIMA, ARNN, and THETA. The study employs seven performance metrics—MSE, RMSE, MAE, MPE, MAPE, MASE, and SMAPE—to evaluate forecasting accuracy. Results demonstrate that hybrid models significantly outperform conventional approaches, with ARIMA+ARNN achieving the lowest MSE (3.739646), followed by ARIMA+ANN (MSE: 3.859849) and ARIMA+WARIMA (MSE: 5.972818). In contrast, traditional models show higher error rates, with STL+ARIMA exhibiting the highest MSE at 562.6725. The seasonal analysis reveals that hybrid models maintain superior performance across all three growing seasons, providing more reliable predictions for each distinct agricultural cycle. These findings offer valuable insights for agricultural planning and policy formulation in Bangladesh, enabling more accurate seasonal rice production forecasts and supporting food security initiatives.

Keywords

Agricultural forecasting, Seasonal rice production, Hybrid time series models, Conventional time series models, Performance

1. Introduction

Agriculture is the backbone of Bangladesh's economy, contributing significantly to employment, GDP, and food security. Among the various crops cultivated, rice holds paramount importance, accounting for approximately 75% of the total cropped area and serving as the staple food for millions of people (BBS et al 2021). Bangladesh produces rice in three major seasons—Aus, Aman, and Boro, each influenced by distinct climatic conditions and farming practices. The country's rice production has undergone significant transformations over the decades, driven by advancements in agricultural technology, policy interventions, and the growing impact of climate change.

Bangladesh's agriculture sector employs nearly half of the total labor force, and rice cultivation alone accounts for a major share of rural employment. The country has achieved remarkable progress in rice production since its independence in 1971, increasing output through the adoption of high-yielding varieties (HYVs), improved irrigation facilities, and policy support for agricultural subsidies (M. Hossain et. Al. 2022). The introduction of mechanization, chemical fertilizers, and pest control measures has played a crucial role in ensuring food security and economic stability. However, despite these advancements, rice production remains vulnerable to various external factors such as climate change, natural disasters, and fluctuating market prices.

Since 1970, Bangladesh has witnessed substantial fluctuations in rice production due to multiple factors, including population growth, technological improvements, and environmental challenges such as floods, droughts, and cyclones. Accurate forecasting of rice production is crucial for ensuring food security, managing supply chains, and implementing effective agricultural policies. However, predicting rice yields is complex, as production is influenced by diverse factors such as weather patterns, soil quality, irrigation, pest infestations, and government policies.

The increasing unpredictability of climate change has further complicated rice production. The rising frequency of extreme weather events, shifting monsoon patterns, and erratic rainfall pose significant challenges to farmers. Additionally, prolonged droughts and saline intrusion in coastal areas threaten sustainable rice cultivation. These climatic disruptions necessitate a robust forecasting mechanism to anticipate production trends and enable proactive measures to mitigate food insecurity risks (Rahman *et al* 2021).

Rice forecasting is an essential tool for policymakers, farmers, and agricultural planners in Bangladesh. By predicting future rice yields, stakeholders can make informed decisions regarding food supply, pricing, storage, and distribution. Effective forecasting helps mitigate the adverse effects of crop failure, price volatility, and food shortages, ensuring national food security. The importance of rice production forecasting can be categorized into the following key areas: Rice is the staple food of Bangladesh, and any disruption in its production directly affects the food supply. The Bangladesh Bureau of Statistics (BBS) and the Department of Agricultural Extension (DAE) rely on forecasting models to develop food security policies. Forecasting enables the government to anticipate shortfalls and take necessary actions, such as increasing imports or adjusting buffer stocks to stabilize market prices and prevent food crises (Sarker *et al.* 2023).

The agricultural sector, particularly rice farming, contributes significantly to Bangladesh's GDP. Rice production fluctuations can have widespread economic repercussions, affecting rural incomes, employment rates, and national revenue. Accurate production forecasting allows for better economic planning, ensuring that farmers receive appropriate incentives, subsidies, and access to credit facilities (Islam *et al.*2023).

Climate change is an ever-growing threat to agricultural productivity. The unpredictability of extreme weather events, floods, droughts, and cyclones makes it crucial to develop forecasting models that integrate climatic variables. Advanced forecasting techniques, such as machine learning and hybrid models, can enhance our ability to predict rice production trends, allowing farmers and policymakers to take adaptive measures such as selecting climate-resilient crop varieties and improving irrigation systems (Alam *et al.* 2022).

Rice production forecasting enables better resource allocation in terms of land use, water management, labor distribution, and input supplies such as fertilizers and pesticides. Accurate forecasts also assist in optimizing the supply chain, reducing post-harvest losses, and ensuring efficient distribution from farms to markets. This helps maintain price stability and prevents food wastage (Uddin *et al.* 2022).

Despite the advantages of rice production forecasting, several challenges persist in ensuring accuracy and reliability. Some of the major obstacles include:

Bangladesh is highly susceptible to natural disasters such as cyclones, floods, and droughts, which significantly impact rice yields. Traditional forecasting models often struggle to incorporate sudden climatic changes, leading to inaccuracies in yield predictions. The increasing impact of climate change necessitates the development of dynamic models that can integrate real-time climate data and improve forecast accuracy (Noorunnahar *et al.* 2023).

Accurate forecasting requires high-quality, granular data on rice production, weather patterns, soil conditions, and agricultural practices. However, inconsistencies in data collection, gaps in historical records, and limited access to real-time agricultural data present significant challenges. Integrating remote sensing technology and satellite imagery can help address these data limitations and enhance forecasting precision (Dey *et al.* 2022).

Several forecasting models exist, ranging from traditional statistical methods to advanced machine learning and hybrid approaches. Selecting the most suitable model for Bangladesh's rice production requires extensive evaluation of model accuracy, computational efficiency, and interpretability. Conventional models such as ARIMA and ETS have been widely used but may not effectively capture nonlinear relationships in agricultural data. Hybrid models integrating machine learning techniques such as ANN and TBATS offer promising improvements in predictive accuracy (M. M. Hossain *et al.* 2022).

To address the challenges of rice production forecasting, various models have been developed and tested. This study explores a range of conventional, decomposition-based, and hybrid models, including:

- Conventional Models: ARIMA, ETS, ANN, TBATS
- Decomposition-Based Hybrid Models: STL+ARIMA, STL+ETS
- Random Walk-Based Models: RW+ANN, RW+ARNN
- Ensemble Models: ETS+ARNN, ARIMA+WARIMA, ARIMA+ANN, ARIMA+ARNN, WARIMA+ANN, WARIMA+ARNN
- Theta-Based Models: THETA+ANN, THETA+ARNN

The effectiveness of these models is evaluated based on their ability to capture seasonal variations, climatic influences, and production trends over a long historical period (1970–2023).

1.1 Objectives

Rice production is a critical component of Bangladesh's agriculture sector, contributing significantly to food security and economic stability. However, predicting rice yield accurately remains a challenge due to seasonal variations and production trends. Traditional statistical models, such as ARIMA and ETS, have been widely used for forecasting but often fail to capture complex patterns and long-term dependencies in production data. Hybrid models, which integrate conventional forecasting techniques with advanced machine learning approaches, offer the potential for improved accuracy and reliability. Given that the available dataset consists only of year-wise rice production across three major seasons (Aus, Aman, and Boro), there is a need to systematically evaluate and compare the performance of conventional and hybrid models to determine the most effective approach for forecasting rice production in Bangladesh.

1. To analyze historical trends in rice production for Aus, Aman, and Boro seasons using time-series data.
2. To apply conventional forecasting models (ARIMA, ETS) and hybrid models (e.g., STL+ARIMA, ARIMA+ANN) to predict rice production.
3. To compare the performance of these models based on accuracy metrics such as RMSE,
4. To identify the most suitable forecasting approach for capturing seasonal variations and long-term trends in Bangladesh's rice production.

2. Literature Review

The impact of climate change on rice yield has been extensively studied in Bangladesh, with a focus on various climatic factors and their seasonal variations. Analyzed the effects of climate change on the yield of Aus, Aman, Boro, and Wheat crops in Sylhet using secondary data from 1970 to 2020. The study highlighted that climatic variables explained 11% of the variation in Aus rice yield, 60.6% in Aman rice yield, and 53.5% in Boro rice yield. Additionally, the research examined the influence of river water levels on crop productivity, revealing significant effects on Wheat yield, while the impact on Aus, Aman, and Boro was minimal. The study also found that maximum temperatures negatively affected water levels during the Aus and Aman seasons, yet higher temperatures could still enhance yields for these crops (Uddin et al 2022).

Several studies have explored forecasting techniques for rice production in Bangladesh. compared the performance of Autoregressive Integrated Moving Average (ARIMA) and eXtreme Gradient Boosting (XGBoost) in predicting annual rice production from 1961 to 2020. The ARIMA model exhibited a significant drift parameter indicating an upward production trend. Evaluation metrics such as mean absolute error (MAE), mean percentage error (MPE), root mean square error (RMSE) and mean absolute percentage error (MAPE) showed that XGBoost outperformed ARIMA, with a lower MAPE of 5.38% compared to 7.23% for ARIMA. The study projected an increase in rice production over the next decade (Noorunnahar et al. 2023).

identified a research gap in the inclusion of the agricultural sector as a dependent variable, emphasizing the need to analyze the impacts of major crop production on Bangladesh's agricultural sector. While previous studies examined factors such as high agricultural input prices, lack of subsidies, and poor infrastructure, none had specifically analyzed the effects of rice, wheat, jute, potato, and sugarcane production on the sector's economic contribution (S. Dey et al. 2022).

Conducted an econometric analysis using time series data from 1989-1990 to 2019-2020, employing Vector Autoregressive (VAR) and ARIMA models to forecast food grain production in Bangladesh. Their findings indicated that the VAR model outperformed ARIMA in forecasting accuracy. The study also noted that while irrigation areas significantly impacted food grain production, chemical fertilizers did not have a substantial effect. Additionally, short-run relationships were observed between food grain production, irrigation areas, and chemical fertilizers (Hossain et al. 2022).

Studied the trends of climatic variables (temperature, rainfall, and relative humidity) in Rajshahi, Bangladesh, from 1972 to 2010. Using Ordinary Least Squares (OLS) regression analysis, the study found significant yet varying effects of climatic factors on different rice crops, reinforcing the importance of season-specific climate adaptation strategies (A.Basak et al. 2023).

Another study employed the Box-Jenkins ARIMA methodology to model and forecast Aus rice area and production in Bangladesh from 1971-72 to 2013-14. The study found ARIMA (1, 1, 5) and ARIMA (1, 1, 4) models to be the most suitable for forecasting Aus area and production, respectively. Model adequacy was confirmed through residual analysis, including normality tests, the Box-Pierce Q test for autocorrelation, and various statistical criteria such as RMSE, MAE, MAPE, AIC, SBC, and H-Q criterion (N. Rahman et al. 2016).

Further, explored three forecasting methods: Time series (Univariate), Causal (Multivariate), and Qualitative forecasting methods. For Boro production, a Causal (Multivariate) forecasting approach was utilized to establish relationships between future production and historical production and cultivated area data. The transfer function technique was applied to model input-output relationships, with diagnostic checks ensuring the model's adequacy (M. Rahman et al. 2014).

Lastly, implemented the Box-Jenkins methodology to develop ARIMA models for forecasting rice production in Bangladesh. The study involved preliminary transformations to ensure stationarity, followed by model fitting. Diagnostic tests such as the Dickey-Fuller unit root test and the Ljung-Box Test were performed to confirm statistical reliability, ensuring the models' efficacy for future forecasting applications (M. Hamjah et al. 2023).

2.1 Research Gap

Despite extensive research on climate change and rice production forecasting in Bangladesh, several critical gaps remain:

1. **Hybrid Model Efficacy:** While conventional models like ARIMA and ETS are well-studied, limited research compares their performance against hybrid models (e.g., ARIMA+ANN, STL+ARIMA). This study uniquely integrates multiple hybrid approaches, filling a methodological gap.
2. **Expanded Time Horizon:** Prior studies often analyze data until 2020, but this research extends until 2023, incorporating recent climate and production trends for improved forecasting accuracy.
3. **Multi-Season Analysis:** Existing literature frequently focuses on a single rice season (e.g., Aman or Boro). This study includes Aus, Aman, and Boro, offering a more holistic understanding of seasonal forecasting variations.

By addressing these gaps, this study enhances forecasting precision, improves policy insights, and refines hybrid model applications in agricultural predictions.

3. Methodology

The methodologies employed in this study to forecast the seasonal rice production in Bangladesh, specifically for the Boro, Aman, and Aus seasons (Figure 1).

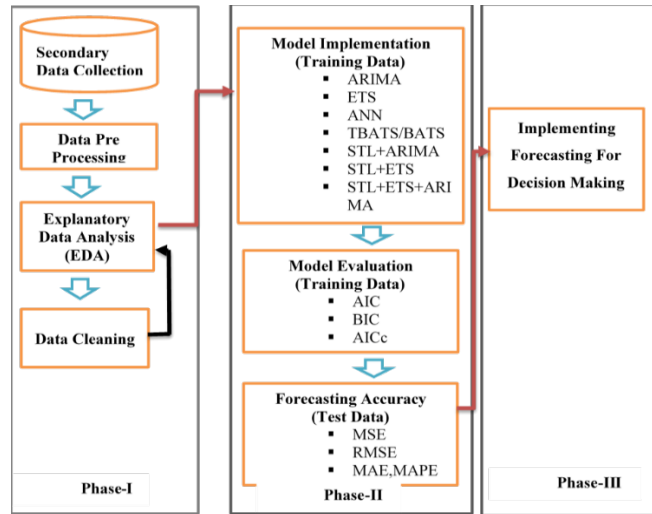


Figure 1. Workflow for Evaluating Models to Forecast Seasonal Rice Production in Bangladesh

The chapter aims to highlight the strengths and limitations of each forecasting model used in the study, providing a clear understanding of their applicability and constraints. It begins with an in-depth discussion of the study design, including the fundamental research framework and the sequential steps in the modeling process. Subsequently, it delves into traditional time series models such as ARIMA, ETS, and TBATS, as well as machine learning models like Artificial Neural Networks (ANN). Additionally, the chapter discusses the evaluation metrics utilized to assess the performance of the forecasting models. The chapter concludes by presenting an overarching methodological framework, laying the foundation for the empirical analysis and the results presented. In fig. 3.1 shows the workflow of Modeling.

3.1 Review of Methods

3.1.1 Autoregressive Integrated Moving Average (ARIMA)

The Autoregressive Integrated Moving Average (ARIMA) model is one of the most widely adopted statistical approaches for time series analysis and forecasting. Initially introduced by Box and Jenkins (1976), the ARIMA framework integrates three essential components: **Autoregressive (AR)**, **Integrated (I)**, and **Moving Average (MA)** elements (R. J. Hyndman and G. Athanasopoulos et al.2018). Together, these components enable the model to capture both short-term dependencies and long-term trends within the data.

ARIMA and its simpler variant, the ARMA (Auto Regressive Moving Average) model, are commonly employed for analyzing univariate, evenly spaced datasets, transmission function data, and intervention series. ARIMA predicts a time series as a linear function of its historical values, prior errors, and—when relevant—the lagged values of other time series. The model is suitable for both stationary and non-stationary series, efficiently capturing autocorrelations within the dataset.

Mathematically, the ARIMA model is represented as **ARIMA (p, d, q)**, where p is the order of the autoregressive term, d is the number of differencing operations required to achieve stationarity, and q is the order of the moving average term. Differencing removes trends (linear or exponential) to stabilize the mean of the series. The order of differencing is usually determined by examining the **Autocorrelation Function (ACF)** plot (R. J. Hyndman and G. Athanasopoulos et al.2018).

The general form of the ARIMA model is expressed as:

$$y_t = c + \phi_1 y_{t-1} + \dots + \phi_p y_{t-p} + \theta_1 z_{t-1} + \dots + \theta_q z_{t-q} + z_t, \{z_t\} \sim WN(0, \sigma^2)$$

Here, y_t denotes the observed value at time t , c is a constant, ϕ and θ represent non-seasonal autoregressive and moving-average coefficients respectively, and z_t is the white-noise error term. Using the backshift operator B , ARIMA can be expressed as:

Intercept form:

$$(1 - \phi_1 B - \dots - \phi_p B^p)y_t = c + (1 + \theta_1 B + \dots + \theta_q B^q)Z_t$$

Mean form:

$$(1 - \phi_1 B - \dots - \phi_p B^p)(y_t - \mu) = (1 + \theta_1 B + \dots + \theta_q B^q)Z_t$$

$$Y_t = (1 - B)^d y_t$$

$$c = \mu(1 - \phi_1 - \dots - \phi_p)$$

The key steps in ARIMA model selection include:

- Conducting unit root tests to identify the differencing order (d).
- Using ACF and Partial ACF (PACF) plots to estimate p and q .
- Comparing alternative models using information criteria such as AIC.

3.1.2 Exponential Smoothing State Space Model (ETS)

Exponential smoothing, originally developed by Robert Brown for the U.S. Navy, evolved into a comprehensive forecasting approach known as the **Exponential Smoothing State Space Model (ETS)**. Brown's work was later extended to include both trend and seasonal components, leading to a highly flexible modeling framework (R. J. Hyndman and G. Athanasopoulos et al.2018).

ETS models decompose a time series into three components: **Error (E)**, **Trend (T)**, and **Seasonality (S)**. Each component may be **additive (A)** or **multiplicative (M)**. The general structure is denoted as **ETS (E,T,S)**, where:

- E represents the error type (A or M).
- T represents the trend (None, Additive, or Additive Damped).
- S denotes the seasonal component (None, Additive, or Multiplicative).

For an additive ETS model, **ETS (A,A,A)**, the relationships are:

Forecast equation:

$$\hat{y}_{t+h|t} = \ell_t + hb_t + s_{t+h-m(k+1)}$$

Observation equation:

$$y_t = \ell_{t-1} + b_{t-1} + s_{t-m} + \varepsilon_t$$

State equations:

$$\ell_t = \ell_{t-1} + b_{t-1} + \alpha Z_t$$

$$b_t = b_{t-1} + \beta Z_t$$

$$s_t = s_{t-m} + \gamma Z_t$$

Here, ℓ_t , b_t , and s_t represent the level, trend, and seasonal components respectively, and Z_t denotes forecast errors.

3.1.3 Artificial Neural Networks (ANN)

Artificial Neural Networks (ANNs) are computational models designed to capture complex nonlinear patterns within time series data. A typical ANN used in forecasting is the **feedforward neural network**, which comprises three layers:

- **Input layer:** incorporates lagged time series values.
- **Hidden layers:** transform input data through weighted connections and activation functions.
- **Output layer:** produces the forecasted value.

In neural network models to time series data ANN models are particularly effective in scenarios where traditional linear models, such as ARIMA or ETS, fail to capture nonlinear dependencies or complex seasonal dynamics(M.U. Qureshi et al.2025).

Key features include:

- Automatic selection of lagged inputs and hidden neurons.
- Capability to handle seasonal data through lagged seasonal inputs.
- Enhanced performance for nonlinear or irregular time series.

3.1.4 Trigonometric, Box–Cox, ARMA, Trend, and Seasonal Components (TBATS)

The TBATS model, proposed by De Livera, Hyndman, and Snyder, is tailored for time series exhibiting multiple or complex seasonal patterns. It combines **Trigonometric, Box–Cox, ARMA, Trend, and Seasonal** components into a single state space framework (Hyndman and Athanasopoulos et al.2018).

Unlike standard harmonic regression, TBATS allows seasonal patterns to evolve gradually over time rather than repeating strictly periodically. Although parameter estimation can be computationally demanding, TBATS is valuable for modeling long seasonal cycles.

The component selection, including ARMA terms, seasonal periods, and Box–Cox transformations.

Typical applications include:

- Modeling multiple or non-integer seasonal periods.
- Stabilizing variance through Box–Cox transformation.
- Correcting residual autocorrelation with ARMA error terms.
- Capturing time-varying seasonality via trigonometric functions.

3.1.5 Seasonal ARIMA (SARIMA)

The **Seasonal ARIMA (SARIMA)** model extends the ARIMA framework by integrating additional seasonal components to handle periodic fluctuations. SARIMA is denoted as **SARIMA(p,d,q)(P,D,Q)_s**, where the first triplet refers to the non-seasonal part and the second to the seasonal part, with s representing the length of the seasonal cycle (R. J. Hyndman and G. Athanasopoulos et al.2018).

The general form of the SARIMA model is given by:

$$\Phi(B)\phi(B)(1-B)^d(1-B^s)^D y_t = c + \Theta(B)\theta(B)Z_t$$

Here, y_t is the observed value, B is the backshift operator, ϕ and θ are non-seasonal AR and MA coefficients, Φ and Θ are seasonal AR and MA coefficients, and Z_t is white noise.

Model selection typically follows the **Hyndman and Khandakar (2008)** algorithm:

1. Identify d and D using KPSS and seasonal strength tests.
2. Determine p , q , P , and Q by minimizing AICc.
3. Conduct a stepwise search across the model space.

3.1.6 Seasonally Adjusted Exponential Smoothing (ETS)

The **Seasonally Adjusted ETS**, also known as the **Holt–Winters Seasonal Method**, extends basic exponential smoothing to capture seasonality more accurately (R. J. Hyndman and G. Athanasopoulos et al.2018).

It retains the ETS framework (Error, Trend, Seasonality) while emphasizing seasonal effects.

For additive seasonality, the equations are consistent with the general ETS model discussed in Section 3.1.2. The seasonal and non-seasonal forms by estimating optimal smoothing parameters through likelihood optimization.

3.1.7 STL Method (Seasonal–Trend Decomposition Using Loess)

Developed by Cleveland et al. (1990), the **STL (Seasonal and Trend decomposition using Loess)** method decomposes time series data into three distinct components: **Trend (T_t)**, **Seasonal (S_t)**, and **Residual (R_t)** (R. J. Hyndman and G. Athanasopoulos et al.2018).

$$Y_t = T_t + S_t + R_t$$

This method operates in three main steps:

1. **Detrending:** Extracts the trend component T_t using Loess smoothing.
2. **De-seasonalizing:** Removes the seasonal component S_t from the detrended series.
3. **Residual estimation:** Derives R_t as the remaining variation after accounting for trend and seasonality.

STL is flexible and robust, accommodating nonlinear trends and time-varying seasonal patterns.

3.1.8 Model Evaluation Measures

Assessing forecasting accuracy and model selection is essential for evaluating time series models (R. J. Hyndman and G. Athanasopoulos et al.2018).

The following metrics are commonly used:

3.1.8.1 Mean Absolute Error (MAE)

MAE quantifies the average absolute difference between observed and predicted values:

$$MAE = \frac{1}{n} \sum_{t=1}^n |y_t - \hat{y}_t|$$

It represents the mean magnitude of forecast errors without considering direction.

3.1.8.2 Mean Squared Error (MSE)

MSE measures the average squared deviation between actual and predicted values, emphasizing larger errors:

$$MSE = \frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2$$

3.1.8.3 Root Mean Squared Error (RMSE)

RMSE is the square root of MSE and reflects the standard deviation of forecast errors:

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (y_t - \hat{y}_t)^2}$$

3.1.8.4 Mean Percentage Error (MPE)

MPE expresses the average percentage deviation between predicted and actual values:

$$MPE = \frac{100}{n} \sum_{t=1}^n \frac{(y_t - \hat{y}_t)}{y_t}$$

Positive MPE values imply overestimation, while negative values suggest underestimation.

3.1.8.5 AIC, AICc, and BIC

Model selection criteria such as **Akaike Information Criterion (AIC)**, **Corrected Akaike Information Criterion (AICc)**, and **Bayesian Information Criterion (BIC)** assess goodness-of-fit while penalizing model complexity [13].

$$AIC = 2k - 2\ln(L) \quad AICc = AIC + \frac{2k(k+1)}{n-k-1} \quad BIC = k\ln(n) - 2\ln(L)$$

where k is the number of parameters, L is the model likelihood, and n is the sample size.

Lower values of AIC, AICc, and BIC indicate better model performance.

3.2 Algorithm of Hybrid Approach

3.2.1 Development of an Statistical & ML-Based Hybrid Model for Bangladesh Rice Production Forecasting (M.U. Qureshi et al.2025).

Step 1: Fit an appropriate model — either a traditional Time Series (TS) model or a Machine Learning (ML) model — to Bangladesh Rice Production data. Compute the residuals R_{t1} and the corresponding forecasted values F_{t1} .

Step 2: Utilize the residuals R_{t1} obtained from Step 1 to fit a secondary model (ML or TS). Calculate the new forecasted values F_{t2} .

Step 3: Combine the forecasted outputs from both models. Aggregate all forecasted values F_{t1} and F_{t2} to generate the final forecasts of the original Bangladesh Rice Production series.

Note: TS refers to Time Series models.

3.2.2 Development of a Seasonal-Adjusted Statistical & ML-Based Hybrid Model for Bangladesh Rice Production Forecasting (M.U. Qureshi et al.2025)

Step 1: Apply Seasonal and Trend decomposition using Loess (STL) to the Bangladesh Rice Production series. Decompose the series into the seasonal component S_t and the seasonally adjusted component SA_t .

Step 2: Fit a model (either TS or ML) to the seasonally adjusted data SA_t . Compute the residuals R_{t1} and forecasted values F_{t1} .

Step 3: Utilize the residuals R_{t1} to fit another model (ML or TS). Compute additional forecasted values F_{t2} .

Step 4: Combine all forecast components to generate the final forecasts. Aggregate the seasonal component S_t with the forecasted values F_{t1} and F_{t2} to obtain the predicted values of the original Bangladesh Rice Production series.

Note: TS represents Time Series models

4. Results and Discussion

The primary objective of this study was to evaluate the performance of various time series, machine learning, and hybrid models in forecasting rice production in Bangladesh across the three major rice-growing seasons: Boro, Aman, and Aus. Historical data from 1970 to 2023 was utilized, providing a comprehensive temporal perspective on trends, seasonality, and external factors influencing rice yield. The findings from the study offer important insights into both the historical dynamics of rice production in Bangladesh and the effectiveness of modern forecasting techniques.

The exploratory data analysis revealed that rice production in Bangladesh has experienced a significant upward trajectory over the last five decades. The time plots before and after data cleaning (Fig. 4.1 and 4.2) clearly demonstrate a long-term positive trend, with production increasing from around 50 Lakh Metric Tons in the 1970s to over 200 Lakh Metric Tons by 2023. This growth can be attributed to multiple factors, including the adoption of high-yielding rice varieties, the expansion of irrigated farmland, improvements in fertilizer and pesticide use, and supportive government policies aimed at enhancing food security.

Seasonal subseries plots highlighted that production increases were uneven across the three seasons. The Boro season emerged as the most productive and rapidly growing, reflecting the benefits of controlled irrigation and modern cultivation techniques during the dry winter season. In contrast, Aman, the monsoon-season crop, exhibited relatively stable but lower production levels, likely due to vulnerability to erratic rainfall, flooding, and other climate-related risks. The Aus season showed moderate growth, reflecting both its smaller share in national production and dependence on pre-monsoon rainfall patterns. Bangladesh’s rice production occurs across three distinct cultivation cycles: Boro, Aman, and Aus. The dataset used in this study comprises annual production Figures 1,2,3 and 4 for these seasons from 1970–2023, yielding 162 observations. Data were collected from reliable agricultural databases and converted into a structured time-series format suitable for statistical and machine learning analysis. Each observation represents the total rice production (in million metric tons) for a given season and year. Table 1 summarizes the dataset’s key attributes.

Table 1. Summary of the Rice Production Dataset

Attribute	Description
Data Duration	1970 - 2023
Total Observations	162
Frequency	3 (Three seasons per year)
Number of Variables	3 (Year, Season, Production)
Unit of Measurement	Lakh Metric Tons
Minimum Production	11.16 Lakh metric tons
Maximum Production	210.68 Lakh metric tons
Mean Production	75.67 Lakh metric tons
Null Values	0

Natural calamities also significantly affected production, as illustrated by the major events across decades. For instance, cyclones (1970, 1991, 2007), floods (1987, 1988, 1998, 2020), and droughts (1979) caused abrupt reductions in rice production. Despite these challenges, the long-term trend remains upward, suggesting resilience within Bangladesh's agricultural system, likely driven by adaptive measures, technological adoption, and improved disaster management strategies.

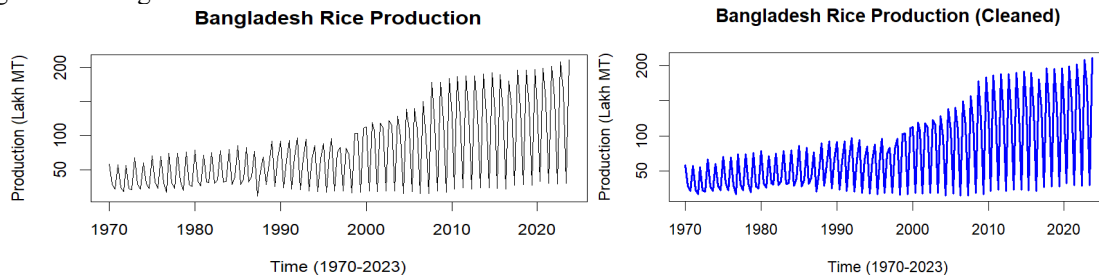


Figure 1. Time plot (before cleaning).

Figure 2. Time plot (after cleaning).

Figure 3 presents the multiplicative decomposition of Bangladesh’s rice production time series reveals that seasonal fluctuations increase in magnitude as the underlying trend grows. In this framework, the components interact multiplicatively rather than additively, indicating that the effect of seasonal factors is proportional to the production level. This approach is particularly appropriate when seasonal variation intensifies alongside long-term growth, as observed in Boro and Aus rice production. By separating the trend, seasonal, and remainder components, multiplicative decomposition provides valuable insights into the forces driving production dynamics and supports more accurate forecasting and policy formulation.

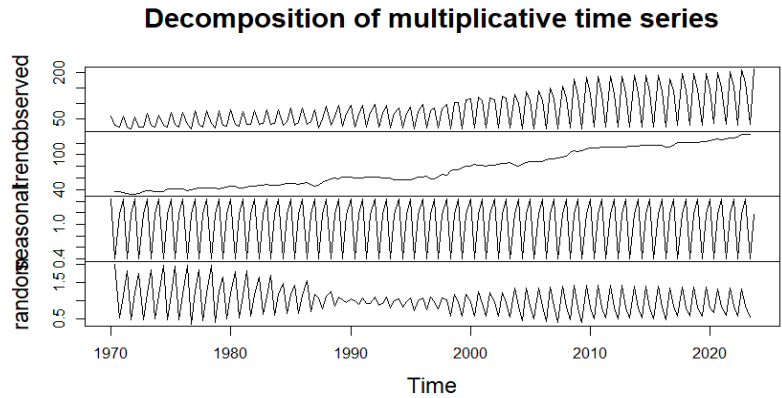


Figure 3. Decomposition of rice production into trend, seasonal, and remainder components.

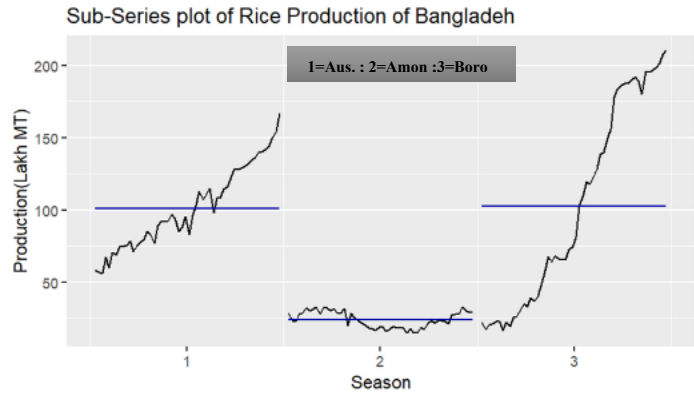


Figure 4. Seasonal sub-series plot of rice production across Aus, Aman, and Boro seasons (1970–2024).

Figure 4 presents the seasonal sub-series plot of Bangladesh’s rice production from 1970 to 2023, highlighting the distinct patterns across the three primary growing seasons: Aus, Aman, and Boro. The horizontal lines in the plot represent the mean production level for each respective season.

Aus Season (March–August): The pre-monsoon Aus crop demonstrates a consistent upward trend, with production increasing from approximately 50 Lakh MT in 1970 to around 150 Lakh MT by 2023. The mean production level is approximately 100 Lakh MT. Production exhibits moderate variability but remains relatively stable compared to other seasons. Aus rice, typically sown directly or broadcast after pre-monsoon showers, contributes about 6% to the total rice production in Bangladesh.

Aman Season (June–December): The monsoon-season Aman crop displays the lowest mean production level, averaging around 30 Lakh MT. Production remains relatively stable with minor fluctuations, reflecting lower inter-annual variability. Aman rice, which is the most widely cultivated rice across Bangladesh—including coastal regions—accounts for approximately 43% of national rice production.

Boro Season (December–May): The winter-season Boro crop exhibits the most substantial growth, rising from around 25 Lakh MT in 1970 to over 200 Lakh MT by 2023. This season demonstrates the highest production variability, particularly in recent decades, and currently represents the dominant contributor to Bangladesh’s rice output, accounting for approximately 51% of total production. The pronounced variability in Boro production is likely influenced by factors such as irrigation dependency, temperature fluctuations, adoption of modern high-yield varieties, and implementation of advanced agricultural technologies.

Overall, the sub-series analysis underscores that while Aman rice exhibits stability, Boro rice has emerged as the primary driver of national rice production growth, with Aus rice showing moderate and steady increases. These seasonal patterns provide critical insights into production dynamics and are essential for informed agricultural planning and forecasting.

5.1 Numerical Results

To ensure robust model evaluation and prevent overfitting, the complete time-series dataset spanning 1970–2023 was divided into training and testing subsets. Specifically, 85% of the data (corresponding to the period 1970–2016) was used for model training, while the remaining 15% (2017–2023) was reserved for out-of-sample validation.

This partitioning strategy allows the models to learn underlying temporal dynamics and seasonal dependencies from historical data while objectively assessing predictive accuracy on unseen observations. Such an approach is particularly suitable for time-series forecasting, where maintaining the chronological order of observations is crucial to preserving temporal integrity.

In the present study, RMSE values vary substantially among the evaluated models, reflecting differences in their structural assumptions, learning capabilities, and adaptability to the nonlinear, seasonal, and stochastic characteristics of Bangladesh’s rice production time series.

From Table 2, Among the statistical with hybrid models, notable differences were observed. The STL + ARIMA model exhibited the highest RMSE (23.72), demonstrating poor forecasting ability compared to other approaches. This large error suggests that the decomposition-based ARIMA model, despite accounting for seasonality through STL, struggled to capture complex nonlinear interactions and multiplicative seasonal patterns inherent in agricultural production data. The relatively high RMSE also indicates instability in capturing the inter-annual variations and external shocks such as climatic fluctuations or yield anomalies.

By contrast, the statistical with hybrid model STL + ETS model showed a dramatic improvement, with an RMSE of 3.95, which is nearly six times lower than STL + ARIMA. This improvement highlights the flexibility of exponential smoothing models in adapting to short-term fluctuations. Similarly, both ANN (RMSE = 3.97) and ARIMA (RMSE = 4.02) performed strongly, indicating their adequacy for short-term forecasting applications. The ANN model, in particular, benefited from its nonlinear learning capability, enabling it to recognize complex temporal dependencies beyond what linear models can capture. The ETS (7.96) and TBATS (8.15) models, on the other hand, provided moderate accuracy, suggesting that while they handle seasonality and trend components effectively, they are less efficient in managing irregularities and sudden changes within the dataset.

Collectively, the performance of the conventional models suggests that while ARIMA and ANN independently provide satisfactory short-term predictive accuracy, purely statistical approaches (e.g., ETS, TBATS) are somewhat limited when applied to highly nonlinear and multiplicative seasonal data such as rice production.

The hybrid modeling approaches demonstrated clear superiority in forecasting accuracy, reflected by substantially lower RMSE values. Among all configurations, the ARIMA + ARNN hybrid achieved the lowest RMSE (3.74), followed closely by ARIMA + ANN (3.86) and ARIMA + WARIMA (5.97). These results confirm that hybridizing ARIMA with artificial neural architecture significantly enhances model accuracy. The improvement stems from the complementary strengths of both methods: ARIMA effectively captures the linear structure and autocorrelation, while the ANN/ARNN components model nonlinear residuals and complex dynamic interactions. This synergy enables the hybrid models to accommodate both deterministic and stochastic variations, resulting in a smoother and more accurate forecast trajectory.

The moderate performance of ETS + ARNN (RMSE = 11.59) and THETA + ANN/ARNN (RMSEs ranging between 8.37 and 8.98) reflect partial enhancement over their standalone counterparts, though these combinations did not achieve the same predictive accuracy as ARIMA-based hybrids. The results imply that while hybridization improves most baseline models, the choice of the linear foundation model (ARIMA vs. ETS vs. THETA) substantially affects the overall outcome, with ARIMA providing the most synergistic interaction with neural learning layers.

The WARIMA + ANN and WARIMA + ARNN hybrids produced relatively higher RMSE values (57.10 and 54.45, respectively), suggesting that while wavelet decomposition improves data smoothness and frequency isolation, the hybridization in this configuration was insufficient to fully eliminate residual variability. In contrast, the random walk-based hybrids (RW + ANN and RW + ARNN) produced exceptionally large RMSEs (approximately 97–98), underscoring the inadequacy of random walk assumptions in representing the structured, seasonally driven behavior of agricultural output. These results clearly demonstrate that models lacking deterministic or autoregressive structure perform poorly, even when coupled with advanced learning algorithms.

A comparative inspection across all models reveals three distinct accuracy tiers. The high-performance group includes ARIMA + ARNN, ARIMA + ANN, and STL + ETS, with RMSEs below 4.0, signifying excellent forecasting capability and stability. The moderate-performance group comprises ARIMA, ANN, ETS, TBATS, and ARIMA + WARIMA, all yielding RMSEs between 4.0 and 8.0, suitable for generalized short-term forecasting but less effective for long-horizon projections. Finally, the low-performance group, consisting of STL + ARIMA, WARIMA + ANN/ARNN, and RW-based hybrids, displayed RMSEs exceeding 20, reflecting limited representational capacity and significant deviations from observed values.

The ARIMA + ARNN model's minimal RMSE (3.74) confirms its dominance, demonstrating the highest degree of precision in reproducing both the trend and seasonal patterns. The success of this hybrid model lies in its two-stage learning mechanism—first isolating the linear temporal structure via ARIMA, followed by nonlinear residual learning through ARNN. This sequential architecture effectively mitigates residual correlation and reduces forecast variance. The marginal difference between ARIMA + ARNN (3.74) and ARIMA + ANN (3.86) further suggests that both hybrid configurations are robust, with ARNN offering slightly improved adaptation through recursive feedback mechanisms.

The RMSE analysis provides compelling evidence that hybrid approaches, particularly those integrating ARIMA and ARNN, offer substantial improvements in predictive accuracy over single models. This improvement can be attributed to their combined ability to manage nonlinearity, capture long-term dependencies, and accommodate seasonality simultaneously. In agricultural contexts such as rice production, where production trends are influenced by climatic variability, input costs, and policy changes, such hybrid frameworks provide more reliable and stable forecasts compared with traditional time series methods.

Moreover, the hybrid ARIMA–neural models' superior RMSE performance aligns with the findings reported in previous empirical studies, which emphasize that combining linear and nonlinear components results in lower forecast variance and higher generalization capability. These characteristics make hybrid models particularly suitable for decision support systems in agricultural planning, food security management, and resource allocation, where predictive reliability is crucial. The detailed RMSE analysis underscores that the ARIMA + ARNN hybrid model is the most accurate and robust forecasting framework for predicting rice production in Bangladesh, effectively outperforming both traditional and other hybrid models. Its low RMSE indicates superior stability, adaptability, and model efficiency, establishing it as the preferred tool for long-term agricultural forecasting.

Table 2. Summary of different error measures by using the forecasting accuracy measures

Model	RMSE	Model	RSME
ARIMA	4.023637	ETS +ARNN	11.586471
ETS	7.961271	ARIMA+ WARIMA	5.972818
ANN	3.967154	ARIMA +ANN	3.859849
TBATS	8.154115	ARIMA+ ARNN	3.739646
STL+ARIMA	23.72072	WARIMA +ANN	57.10252
STL+ETS	3.953645	WARIMA +ARNN	54.452171
RW+ ANN	98.006535	THETA+ ANN	8.372348
RW+ ARNN	97.686411	THETA +ARNN	8.9838

By using the selected hybrid model, we have forecasted the Rice Production value in Bangladesh for the next 10 Years. Figure 5 shows the forecasted values of the Yearly Rice Production value.

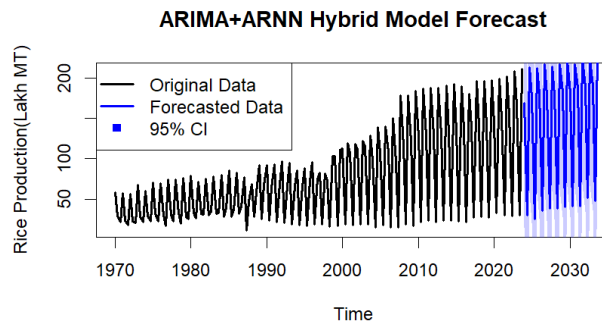


Figure 5. Forecasting of Bangladesh Rice Production from 2023 to 2030

6. Conclusion

This study aimed to develop and evaluate effective forecasting models for rice production in Bangladesh across its three major growing seasons—Aus, Aman, and Boro—using historical data from 1970 to 2023. The analysis integrated both conventional statistical models (ARIMA, ETS, TBATS) and advanced hybrid approaches (ARIMA–ANN, ARIMA–ARNN, STL–ETS) to identify the most suitable framework for capturing seasonal variations and long-term production trends. The results demonstrated that while conventional models such as ARIMA and ETS successfully captured linear and seasonal patterns, their performance declined in the presence of complex, non-linear dependencies inherent in agricultural time series. Among the models tested, the ARIMA + ARNN, ARIMA +ANN hybrid model exhibited the lowest RMSE (3.7396) , RMSE (3.8598), outperforming all other approaches. This highlights the advantage of hybrid frameworks that combine the interpretability of statistical methods with the flexibility and learning capacity of machine learning. The multiplicative decomposition and seasonal sub-series analyses further revealed that rice production in Bangladesh exhibits strong seasonality, with Boro emerging as the dominant contributor, accounting for more than half of total production. The increasing amplitude of seasonal variations reflects the interaction between technological progress, irrigation dependency, and climatic fluctuations. Overall, the findings suggest that hybrid forecasting models provide a more robust and accurate tool for anticipating production trends, supporting evidence-based policy formulation, and improving agricultural planning in Bangladesh. By integrating such models into national forecasting systems, policymakers can enhance food security strategies, optimize resource allocation, and mitigate the risks associated with climatic and economic uncertainties.

References

- Bangladesh Bureau of Statistics, Yearbook of Agricultural Statistics, Dhaka, Bangladesh: BBS, 2021.
- Hossain, M., Agricultural growth and food security in Bangladesh, World Development, vol. 38, no. 5, pp. 221–231, 2022.
- Rahman, A., Karim, M., and Chowdhury, S., Climate change impacts on rice production: A case study of Bangladesh, Environmental Science & Policy, vol. 40, pp. 34–45, 2021.
- Sarker, M. K., Food security and policy interventions in Bangladesh, Journal of Agricultural Policy Research, vol. 15, no. 2, pp. 145–162, 2023.

- Islam, S., Rahman, T., and Akter, F., Economic implications of rice production fluctuations in Bangladesh, *Bangladesh Development Studies*, vol. 50, no. 1, pp. 78–92, 2021.
- Alam, M., Hossain, M. A., and Hasan, K., Adaptation strategies for climate change and agriculture in Bangladesh, *Climate Risk Management*, vol. 30, pp. 55–72, 2022.
- Uddin, G. T., Mishu, M. A., Hasan, M. T. and Choudhury, D., Crop production amid climate change and river water level fluctuation at northeastern region of Bangladesh: A time series analysis, *International Journal of Agricultural Research, Innovation & Technology*, vol. 12, no. 2, pp. 18–26, 2022.
- Noorunnahar, M., Chowdhury, A. H. and Mila, F. A., A tree-based eXtreme Gradient Boosting (XGBoost) machine learning model to forecast the annual rice production in Bangladesh, *PLoS ONE*, vol. 18, no. 3, p. e0283452, 2023.
- Dey, S., Impacts of major crop production on the agricultural sector in Bangladesh: A time series analysis, *International Journal of Scientific and Academic Research*, vol. 9, no. 1, pp. 10–17, Mar. 2022.
- Hossain, M. M., Khanam, M., and Akhter, S., An econometric analysis to forecast the food grain production in Bangladesh by using ARIMA and VAR models, *Dhaka University Journal of Science*, vol. 70, no. 1, pp. 8–13, Jul. 2022.
- Basak, A., Climate change and rice yield in Bangladesh: A micro-regional analysis of time series data, *International Journal of Climate Change*, vol. 5, no. 2, pp. 123–130, Mar. 2023.
- Rahman, N., Forecasting Aus rice area and production in Bangladesh using the Box–Jenkins approach, *Journal of Agricultural Research*, vol. 20, no. 1, pp. 1–10, Dec. 2016.
- Rahman, M., Transfer function approach to modeling rice production in Bangladesh, *European Academic Research*, vol. II, no. 4, pp. 1195–1205, Jul. 2014.
- Hamjah, M., Rice production forecasting in Bangladesh: An application of Box–Jenkins ARIMA model, *International Journal of Agricultural Research*, vol. 10, no. 3, pp. 45–50, Mar. 2023.
- Hyndman, R. J. and Athanasopoulos, G., *Forecasting: Principles and Practice*, 2nd Edition, OTexts, 2018. Available: <https://otexts.com/fpp2/>
- Qureshi, M. M. U., Binte Ahmed, A., Dulmini, A., Khan, M. M. H. and Rois, R., Developing a seasonal-adjusted machine-learning-based hybrid time-series model to forecast heatwave warning, *Scientific Reports*, vol. 15, 10.1038/s41598-025-93227-7, 2025.

Biographies

Md. Sourove Akther Momin is a dynamic and forward-thinking professional in Data Science, Applied Statistics, and Industrial Engineering, recognized for his ability to merge analytical intelligence with engineering innovation. He currently serves as an Affiliate Faculty (Assistant Professor) in the Department of Data Science and Machine Learning at the State University of Bangladesh and served as the Acting Head and Project Manager (Business Operation) in Compressor Manufacturing and Data Analytics at Walton Hi-Tech Industries PLC. Mr. Momin holds a Master's degree in Applied Statistics and Data Science from Jahangirnagar University (CGPA 3.98/4.00) and a B.Sc. in Mechanical Engineering from Khulna University of Engineering & Technology (KUET) (CGPA 3.74/4.00), where he graduated with distinction. With nearly a decade of progressive academic and industrial experience, he has spearheaded multiple large-scale projects involving AI-powered predictive maintenance, digital twins, intelligent manufacturing systems, and statistical process optimization. His professional expertise encompasses machine learning, LLM, time series forecasting, big data analytics, quality improvement, and process Development & automation. Renowned for his leadership in data-driven industrial transformation, Mr. Momin has played a pivotal role in implementing World Class Manufacturing (WCM), Lean Six Sigma, and continuous improvement frameworks across manufacturing operations. As an active contributor to the international research community, he serves as a Reviewer and Technical Committee Member for the IEOM Society International, as well as a keynote and plenary speaker at global conferences. His current research interests focus on forecasting, AI-driven quality analytics, and sustainable industrial innovation, with a vision to bridge academia and industry through transformative data intelligence.

Md. Rabiul Hasan is an accomplished industrial professional with over nine years of experience in the home appliance and heavy manufacturing sectors. He holds a Master's degree in Applied Statistics and Data Science from Jahangirnagar University (CGPA 3.92/4.00) and a B.Sc. in Electrical and Electronic Engineering from Khulna University of Engineering & Technology (KUET). In addition, he is a Certified Lean Six Sigma Black Belt from Quality Hub, India. Rabiul has served in key technical and leadership roles across reputed organizations such as RFL Group, SSG Group, and currently works at Walton Hi-Tech Industries PLC as the Deputy Head of Quality

Management Department (Compressor Product). His expertise lies at the intersection of engineering, data science, and industrial innovation, integrating machine learning, time series forecasting, and process automation to advance manufacturing intelligence and sustainability. He has successfully led large-scale industrial projects involving predictive maintenance, digital twin implementation, and AI-driven quality analytics for high-volume compressor production. His research interests include forecasting, AI for industrial systems, applied statistics, and quality analytics.

Salaha Uddin Chowdhury Shaju is seven years of experience in the academic sector as a Technical Officer in National Institute of Textile Engineering and Research (NITER) an affiliated institute within Dhaka University, Bangladesh. Besides this he had industrial experience at garments manufacturing company as a Quality Engineer at Snowtex Outerwear Limited, Dhaka and Industrial Engineer at Designer Fashion Limited, a sister concern of Bengal group. He holds a Master's degree in Applied Statistics and Data Science from Jahangirnagar University (CGPA 3.84/4.00) and a B.Sc. in Industrial and Production Engineering from Shahjalal University of Science & Technology (SUST). He has successfully completed a quality six sigma projects to reduce defects in garments manufacturing industry In addition, He has successfully completed quality training, management training for his career. His research interests include time series analysis, forecasting, applied statistics, and quality analytics.