FORECASTING OF MAIZE PRODUCTION IN BANGLADESH USING TIME SERIES DATA

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ABSTRACT

Maize has been gaining importance as one of the major grain crops in Bangladesh in recent years. Due to its multiple uses, i.e., food, feed and other industrial uses, maize production and its possible trend have created great interest among the policy planners. This study aims to forecast future production of maize in Bangladesh using both Box-Jenkins autoregressive integrated moving average (ARIMA) and mixed model approach (dynamic regression model) using secondary yearly data, for the growing seasons 1970-71 to 2019-20, published by the Bangladesh Bureau of Statistics (BBS). Our analyses suggest that ARIMA (0, 2, 1) is the best model for forecasting maize production all over Bangladesh. However, when the area of maize is considered the mixed model with ARIMA (1, 0, 0) performs better than the univariate ARIMA (0, 2, 1) model. The length of the 95% confidence interval of the forecast values of the mixed model is smaller than that of the ARIMA model indicating its better predictive performance. These forecast values will be useful for planning resources and making appropriate decisions regarding imports and exports by the government before harvesting.

Keywords: Maize, ARIMA model, mixed model, forecasting

I. INTRODUCTION

Among the prominent cereal crops that are being cultivated in Bangladesh, maize (Zea mays L.) occupies a significant position in terms of production, cultivation and positive trend in growth. Due to its diversified use as food and feed, and other industrial uses, maize has been regarded as an emerging crop for this region. The demand for maize has been rising steadily year after year. In the last three years, from 2017–2018 to 2019–2020, wheat acreage, production, and productivity have declined, even though during the same duration, the results for maize have risen. In Bangladesh, maize has now supplanted wheat as a foremost grain crop after rice (BBS, 2020).

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Although wheat and rice are two of the most important foods in Bangladesh, their production cannot keep up with the country's expanding population. It is widely acknowledged that with a view to meet up with the demands of Bangladesh's growing population, food intake must be slightly more varied in order to reduce the country's concentration on rice and wheat. To accomplish this, it is important to emphasize crop production that yields the most nutrients per unit of area and per unit of time (Hossain et al. 2016). Maize's higher nutritional quality makes it a potential source of nutrients for the increasing population Bangladesh. The demand for maize is rising steadily on both a national and international level due to its numerous uses. Food shortages could be greatly reduced if Bangladeshis' strict rice-only diet could be changed to one that included maize. In order to make the crop gradually marketable and sustainable, an intelligent plan is needed because it is a crop with a lower cost and higher yield when compared to wheat and rice (Moniruzzaman et al. 2009). Uddin et al. (2015) carried out research to develop the maps and union level digital database of maize cultivations areas during the season 2011-12 at Pirgonj in Thakurgaon district of Bangladesh. They also showed that maize cultivation is rising vastly around Bangladesh, especially in northern part in Bangladesh. Hasan et al. (2008) examined the way Bangladesh's two main cereal crops, maize and wheat, changed and became more unstable in terms of yield, production, and area. In addition to developing crop technology to increase productivity, ensuring growers receive attractive prices requires both long- and short-term policies for yearly export and import (Kumar et al. 2020).This usually requires a reliable and precise pre-harvest forecast of crop production. So, short term crop production forecast is essential decision making and management system for Government. This study tries to compare the precision of ARIMA and mixed model and also recommend the most accurate model for predicting Bangladesh's maize production. In regard to Government effort to ensure food security, early estimate/forecast of maize is important to take on import export of maize. The current research is expected to fill in research gap in this respect.

Several methods are available for predicting the crop production for time series data but we used Auto Regressive Integrated Moving Average (ARIMA) and mixed model approach for profuse investigation. Forecasting is used to help with decision-making and facilitate effective and efficient future planning. In this study, the ARIMA model is also employed as a benchmark model for comparing the predictive capabilities of the regression model. Sarika et al. (2011) used the ARIMA model to simulate and forecast India's production of pigeon peas. In order to assess the stability and long-term viability of sugarcane production in the Indian state of Bihar, Paswan et al. (2022) employed ARIMA and Artificial Neural Networks (ANN) models. Based on the lowest values of AIC and BIC, the ARIMA (1, 1, 0) model is the most suitable for forecasting and was presented for estimating sugarcane production from 2020 to 2025. Mishra and Singh (2013) used the ARIMA approach and ANN to estimate groundnut oil prices in Delhi. The ARIMA model was used by Kumari et al. (2014) to forecast the yield of rice in India. Using the ARIMA approach, Naveena et al. (2014) estimated India's production of coconuts. To find suitable solutions, many studies have used the ARIMA approach to forecast demand in terms of domestic consumption, imports and exports (Muhammed et al., 1992; Shabur and Haque, 1993;

Sohail et al. 1994). Box-Jenkins model was used by Najeeb et al. (2005) to calculate Pakistan's wheat production and area. ARIMA models outperformed deterministic models for predicting pigeon pea yield in India (Rachana et al. 2010). Rathod et al. (2018) employed ARIMA model to predict yield of banana and mango of Karnataka, India. According to Biswas et al. (2013), the ARIMA (2, 1, 3) model for the gross area of rice cultivation in West Bengal, India, is the one that fits data the best, while ARIMA (2, 1, 1) is the model that fits data the most for rice production. For predicting groundnut productivity in the Junagadh region of Gujarat, India, Kumar et al. (2020) utilized the same modelling approach.

The Box-Jenkins modelling approach was utilized in several earlier studies about various agricultural crops in Bangladesh to assess and forecast crop production. Hossain et al. (2016) carried out a study in Bangladesh to predict potato production. The study revealed the appropriate model using the Box-Jenkins approach in predicting future potato production. The research attempted to explore the most fitted ARIMA approach to predict the production of Boro rice in Bangladesh from 2008–2009 to 2012–2013 and found three best ARIMA model for Boro rice production respectively (Rahman, 2010). Forecast Bangladesh's production of food grains using the ARIMA and Vector Autoregressive (VAR) models (Hossain et al., 2022). On the other hand, the forecasting performance of mixed model (considering area as an independent variable) for four crops e.g., Aus, Aman, Boro and Potato is better than the univariate econometric model ARIMA in Bangladesh. In this study, the estimated overall rice production for the 2015–2016 financial year (combined Aus, Aman, and Boro rice) is nearly equal to the country's production (AMIS, 2017). The only option to further expand agricultural production is to grow high-productivity crops like maize. In order to alleviate pressure on rice, the government has been attempting to diversify eating habits and promote the use of other cereal crops like maize. Maize can be played a significant role in this situation as a flexible and alternate food crop for Bangladesh. As a result, it is crucial to estimate the output of food grains, which is exactly why we conducted this study. The purpose of this study is to find the ARIMA approach that may be applied to predict maize production in Bangladesh. It will be compared to a mixed model (a dynamic regression model).

II. MATERIALS AND METHODS

Data source

The study used secondary data, compiled by the Bangladesh Bureau of Statistics (BBS) from 1970-71 to 2019-20, on yearly maize area (hectare) and maize production (metric tons) in Bangladesh (sum of Rabi and Kharif growing seasons).

ARIMA model

The auto regressive (AR) integrated moving average (MA), commonly termed as ARIMA, was applied for short-term prediction crop production at national level. Ultimately, integrated approaches of crop prediction are essential to be used for ultimate forecast. The Box-Jenkins method was utilized to fit the ARIMA model for time series forecasting. The steps of the modelling approach are presented below in Figure 1.

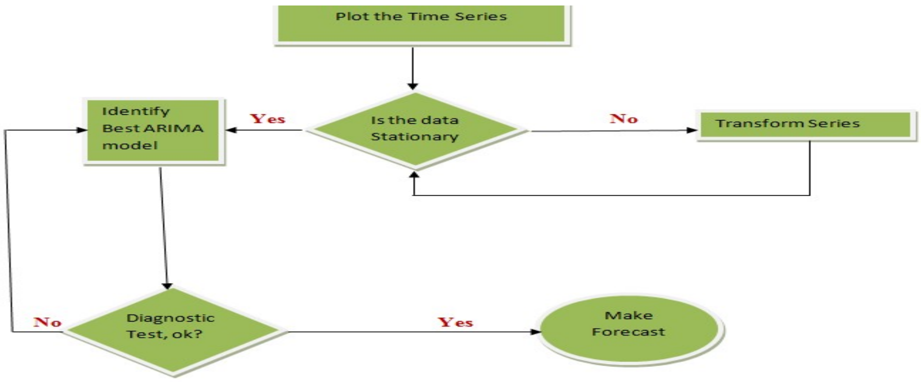


Figure 1: Steps of the ARIMA model (Box-Jenkins iterative approach) flow chart

ARIMA typically outperforms deterministic growth model for short-term prediction in time series models (Rahman et al. 2013). Typically, in the ARIMA modelling firstly, a tentative model is selected (identification); secondly, parameters are estimated using the data (estimation); and finally, some diagnostic tests are performed (diagnostics) before estimating future data points (prediction) using the fitted model. Plotting of the data was applied to detect any unusual observations. For achieving stabilized variance among the time series data, possible transformation of the data is necessary. If the time series non-stationary, the stationarity of the series is to be ensured by means of seasonal and non-seasonal differencing. Once stationarity has been reached, the autocorrelation and correlogram should be examined to determine whether any patterns still exist. It has previously been possible to diagnose the order of differencing, and the differenced univariate time series may be generated using both the frequency-domain and time-domain approaches (Cressie, 1988). Estimating the parameters of the model is the second step. The parameters of the models were estimated using the maximum likelihood estimation approach. The third stage is to assess how well the selected model fits the data. Adopting the correct ARIMA (p, d, q) model so that the residuals projected from this model are white noise requires significant skill. In order to diagnose the model, it is necessary to predict the autocorrelations of the residuals. These can also be evaluated under the null hypothesis that the autocorrelation coefficient is zero using the chi-square test (Ljung and Box, 1978).

The ARIMA model for the study is as follows:

$$\Delta^d Production_t = \alpha_0 + \sum \alpha_p Production_{t-p} + \sum \lambda_q Error_{t-q} + Error_t$$

Where Δ denotes the time series differencing. Where, p stands for autoregressive, d stands for differencing, and q stands for moving average orders respectably.

Mixed model approach

According to Pankratz (1991), a mixed model approach is dynamic in nature that can be used to determine how independent variables impact the response variable of interest. A regression model that includes lagged values of the independent variable(s) is known as a Mixed Model. According to AMIS (2017), this model is used to forecast what will happen to the predictor variable if the independent variable changes. Fitting a multiple regression model using the following specifications is the first step in identifying the most suitable mixed model approach:

$$Y_t = \alpha + \beta_0 X_t + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \cdots + \beta_k X_{t-k} + N_t$$

Where, Y_t refers to the dependent variable; X_{t-k} means the explanatory variable with the time-lag $k = 0, 1, 2, \ldots, K$; $\beta_0, \beta_1, \beta_2, \ldots, \beta_k$ are the regression coefficients and ARIMA process represent as N_t. The useful information is that the rolls of times (past) lag i.e., $X_{t-1}, X_{t-2}, X_{t-3}, \ldots, X_{t-k}$ in explaining the movement in Y_t. Maximum likelihood method is applied for estimating mixed model parameters (Akpan et al. 2016)

If the errors of regression seem non-stationary, differencing of the variable must be applied in the second step. The lower-order ARIMA model for the errors was used to fit the model yet again. The third step is to determine how many lag-affected independent variables will affect the forecast variable if the errors exhibit stationarity at this time. The computation of regression model errors and the identification of an appropriate ARMA approach for the error series constitute the fourth step. The fifth step re-fit the whole model using the transfer function model for independent variables and the new ARMA approach for errors. Finally, the sixth step is to test the adequacy of the fitted model by collating the residuals (Makridakis et al. 1998). As, after systematic investigation, the study has considered area in mixed model approach, the final mixed model functional form of the study is as follows:

$$\Delta^d Production_t = \alpha_0 + \sum \alpha_p Production_{t-p} + \beta_i Area_{t-i} + \sum \lambda_q Error_{t-q} + Error_t$$

Where β_i the coefficient of the ith is lagged independent variables; α_p is the coefficient of pth lagged response variable; λ_q is the coefficient of qth lagged error, and α_0 is the constant.

If the Ljung-Box test indicates that white noise affects the residuals, then the model with the largest R^2 value and the smallest root mean square error (RMSE), mean absolute percentage error (MAPE), and Bayesian information criterion (BIC) can be considered the best model.

Best model selection indicator

Any time series model, there are several summary statistics obtainable to assess the prediction errors. So, for maize production try to detect top model for Bangladesh applying the following extant model detection indicator:

Theil (1961) first proposed the concept of the coefficient of determination (R^2) as-

$$R^2 = \frac{\text{Regression sum of squares}}{\text{Total sum of squares}} = \frac{\text{RSS}}{\text{TSS}} = 1 - \frac{\text{ESS}}{\text{TSS}}$$

In interpreting R^2, it is normally considered the most fitted model when R^2 value is the largest.

The Bayesian Information Criterion (BIC) is a method for choosing a model for a certain set of data from a group of models.
The function of BIC is as follows:
BIC= $-2 * (\text{LL}) + i \times \log(N)$
Where LL denotes the log-likelihood of the model, i denote the number of parameters of the model and N is the number of examples of training data set.
Root mean square error (RMSE) is denoted as follows:

$$\text{RMSE} = \sqrt{\frac{1}{\text{n} - \text{k}} \sum_{t=1}^{n} \varepsilon_i^2}$$

Where the sample size and number of estimated parameters are presented by n and k.

The mean absolute percentage error (MAPE) is a statistical measure used to evaluate the accuracy of a forecasting method. The function of MAPE is:

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{\hat{E}_t}{Y_t} \right| \times 100$$

Where n represents the total number of observations is, Y_t is the observed value and $\hat{E}_t$ is the difference between the observed and estimated value.

III. RESULTS AND DISCUSSION

The time series plot of maize production shows that the production of maize (including Rabi and Kharif) is fluctuating over the time (Figure 2). The fluctuation with time denotes the data series seems to be non-stationary (mean, variance and autocorrelation are time dependent). Specially, maize production increased frequently in the last 11 (eleven) financial years during 2008-09 to 2019-20. Increasing and decreasing trends of maize production present that the variance is unstable which means non-stationary the maize production data series because its mean and variance depend on time. It is also obvious that the production time series of maize is non-stationary as the mean and variance are not constant over time.

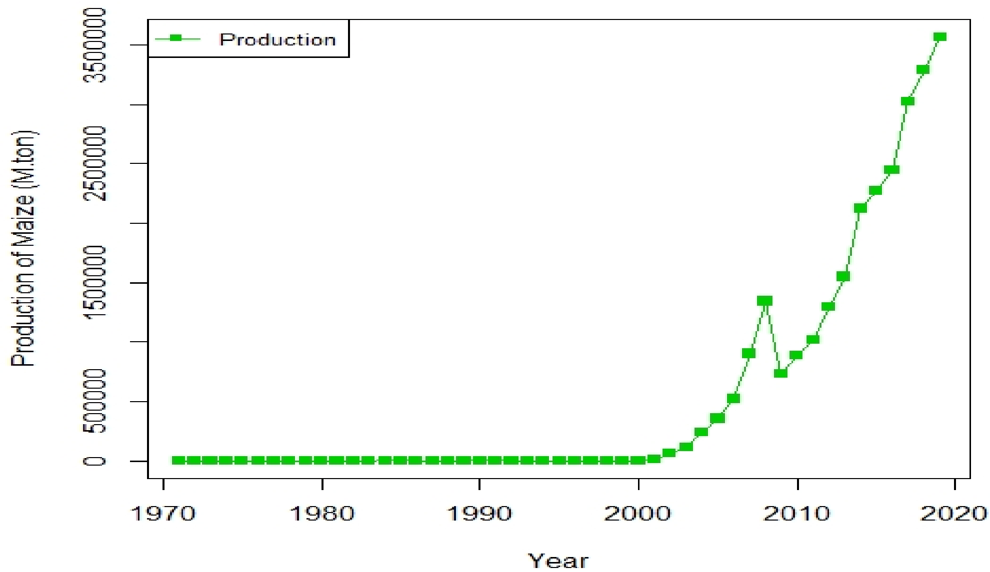


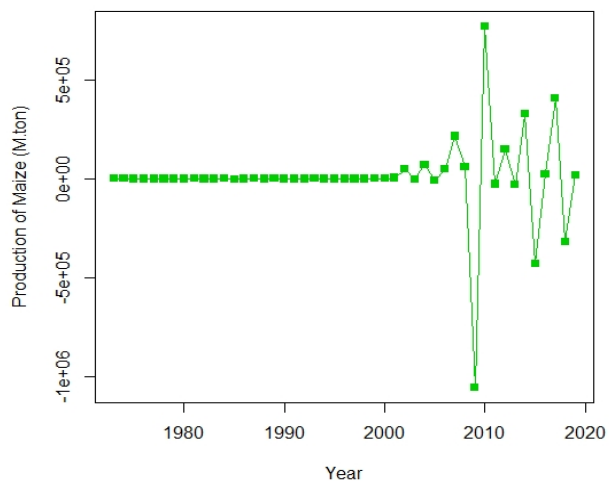
Figure 2: Production of maize during the growing season 1970-2020

The stationarity of maize in Metric Tons (MT) from the fiscal years 1970–1971 to 2019–20 has been examined using Augmented-Dickey-Fuller (ADF) test, as well as Phillips-Perron (PP) test. According to the PP test with $P(|\tau| \geq -63.2099) < 0.01$ and the ADF test with $P(|\tau| \geq -6.3608) < 0.01$ at 5% level of significance, the data sets are found stationarity and no longer unit root after the second differentiations. In different years' data, maize productions are stationary at the second differences which is presented in Table 1.

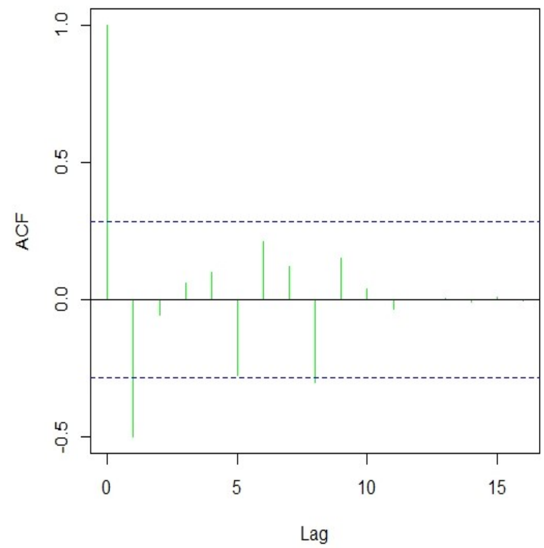
Table 1: The stationary checking of the production data series of maize (in MT)

Order of differencing	ADF Test		PP Test		Remarks
	Statistic	P-value	Statistic	P-value	
None	2.38	0.99	4.05	0.99	Not Stationary
First	-2.53	0.36	-49.3	0.11	Not Stationary
Second	-4.82	0.01	-58.9	0.01	Stationary

It is obvious that the production data sets of maize show a rising trend, but unstable variance (Figure 2). We note that after the second differences, the production data sets of maize exhibits steady variance, which means that the differenced data sets turn stationary (Figure 3.a). The AM process is symbolized through switching of autocorrelation functions' positive and negative values (Fig. 3.b), and the exponential degrade of the partial autocorrelation function (Figure 3.c). The PACF with significant spike at lag 1 and 2 as well as autocorrelation function with significant spike at lag 1 expose that autoregressive coefficient not present and first order moving average are fruitful of production of maize in Bangladesh. Trial-and-error techniques might be used to confirm the aforementioned results.



a



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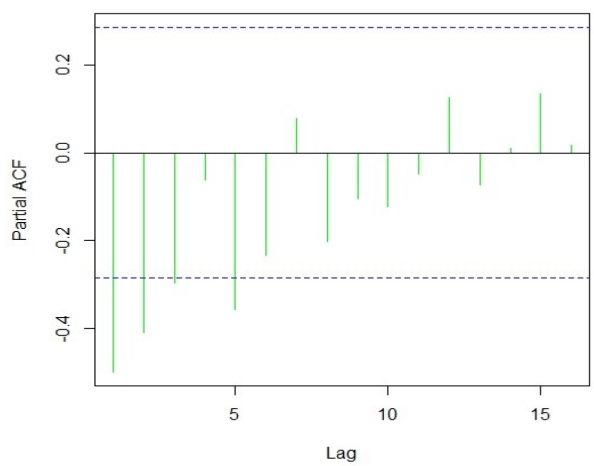

c

Figure 3: (a) the second differentiation plot's time series (b) the ACF plot's correlogram and (c) the PACF plot's correlogram at second differenced maize production in Bangladesh.

Table 2: Model selection with different orders

ARIMA Model		Mixed Model Approach	
Model	**AICc**	**Model**	**AICc**
ARIMA (1,2,0)	1309.35	ARIMA (2,0,2)	1299.38
ARIMA (0,2,1)	**1295.36**	ARIMA (2,0,1)	1298.67
ARIMA (1,2,1)	1297.09	**ARIMA (1,0,0)**	**1293.25**

Though, it observed that ARIMA (0, 2, 1) with AIC=1295.09, AIC_C=1295.36 and BIC= 1298.83 is the most chosen model for ARIMA and for Mixed model, i.e., ARIMA (1, 0, 0) with AIC=1292.73, AIC_C=1293.25 and BIC= 1298.47 is the most selected model for predicting production of maize in this country like Bangladesh (Table 2).

The best model is selected by considering the highest R^2 value and the smallest value of RMSE, MAPE and BIC where Ljung-Box test reveals that the residuals go after white noise, i.e., autocorrelations are zero. ARIMA model and mixed-model are presented in Table 3 for predicting maize production on account of separate model selection indicator.

Table 3: Model selection indicator for detecting the most requisite model

Model	R^2	RMSE	MAPE	BIC	Ljung-Box Q Statistic	Ljung-Box Q P-value
ARIMA (0, 2, 1)	0.97	162586	15.85	1298.83	14.16	0.117
Mixed-model with ARIMA (1, 0, 0)	0.99	92633	82.73	1298.47	10.33	0.243

We observe that, ARIMA (0, 2, 1) is the most chosen model for predicting production of maize among the alternative models tested under Box-Jenkins methodology (Table 3). ARIMA model uses for time series data for crop production (dependent variable) but not apply crop area. Conversely, mixed-model approach makes out the part of predictors in influencing dependent variable. Therefore, this depends on response variable like crop production, including explanatory variable like crop area for time series data. Here, the mixed-model is better fitted than ARIMA for predicting maize production owing to distinct model selection indicator. Except MAPE, the mixed-model is the most suited model for forecasting production of maize rather than ARIMA (0, 2, 1) in Table 3. Mixed model for production of maize comprises area of the production and ARIMA (1, 0, 0) as the predictor.

As shown in Figure 4.a, a variety of pictorial checks of the residuals for the fitted ARIMA (0, 2, 1) model revealed no discernible pattern and, as a result, no autocorrelation among the residuals.

ARIMA approach **Mixed-model approach**

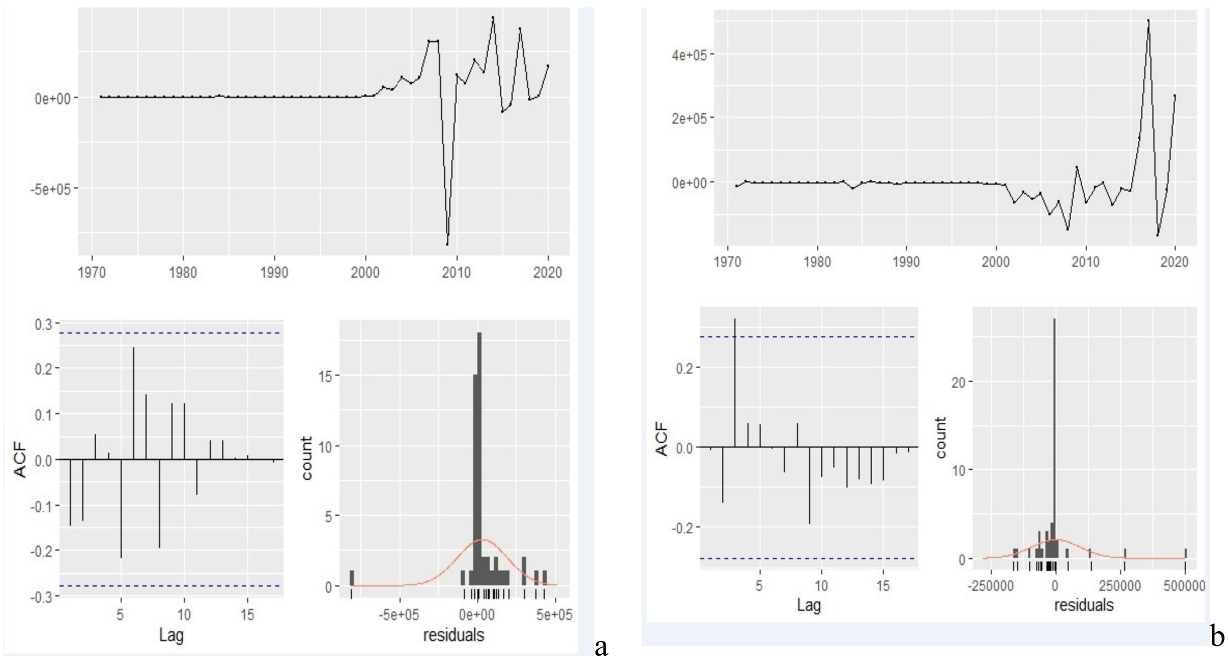

Figure 4: Residuals plots and a histogram with normal curve; a. ARIMA approach; b. Mixed-model

The normalized histograms of the residuals for the adjusted ARIMA (0, 2, 1) and the mixed model approach approximately indicate that the residuals are normally distributed (Figure 4 (a, b)). While mixed model may be applied to identify the emphasis of the time lag of explanatory variable in influencing the movement in dependent variable so, it observed that our fitted mixed model i.e., ARIMA (1, 0, 0) is most suited on account of normality rather than ARIMA (0, 2, 1) model and is adequate to predict the maize production in Bangladesh. There was no study to forecast maize production in Bangladesh using those methods except three category of rice (Aus, Aman and Boro) and potato (AMIS, 2017).

Different varieties of maize are available in Bangladesh whose plantation times are also different. So, forecasts are necessary for separate phases. It is significant to forecast crop production at sequential steps like planting, growing and harvesting period. ARIMA may be used for forecasting production of crop in plantation stage (or earlier). Furthermore, mixed-model approach may be used when the information on area under maize cultivation are available. On the basis one of the most effective predicting indicators, forecast value of ARIMA and mixed model approach as well as 95% confidence level for five financial seasons for production of maize are presented in Table 4.

Table 4: Forecast value of the maize production (in MT) from the year 2020-21 to 2024-25

Year	ARIMA (0, 2, 1)			Mixed-model with ARIMA (1, 0, 0)		
	Forecast	Lower limit	Upper limit	Forecast	Lower limit	Upper limit
2020-21	4327360	3998684	4656035	4202586	4017285	4387887
2021-22	4639413	4125567	5153260	4408440	4166974	4649906
2022-23	4951467	4260942	5641993	4629115	4355184	4903045
2023-24	5263521	4394509	6132533	4861651	4567172	5156131
2024-25	5575575	4523006	6628144	5103710	4795697	5411722

Table 4 indicates that the maize production will be 4327360 MT in 2020-21 and if the present situation continues the production of maize of Bangladesh in 2024-25 would be 5575575 MT on the basis of ARIMA model forecasting. But the mixed-model approach exposes that the production of maize will be 4202586 MT in 2020-21 and will reach up to 5103710 MT in 2024-25 considering land area and lag of land area as the independent variables. The length of the confidence interval of the predicted value for mixed-model approach is lower than that of the ARIMA model.

Figure 5 displayed the visual contrast of the actual production data and the expected production data. It is clear from the original maize production data for ARIMA that production was initially equal, occasionally showed a slight upward trend, and again after the year 2000 showed an abrupt upward tendency. The predicted maize production data differs slightly from the original set of data which presents the original production data in the same manner (Figure 5). Similarly, the original and forecast maize production data for mixed-model approach initially shows equal production and after some times forecast maize production data shows upward tendency than original data. Also, forecast efficiency of mixed-model approach is better than ARIMA. So, it can be judged that the mixed-model approach will give more appropriate interval estimation rather than ARIMA for maize production (Figure 5).

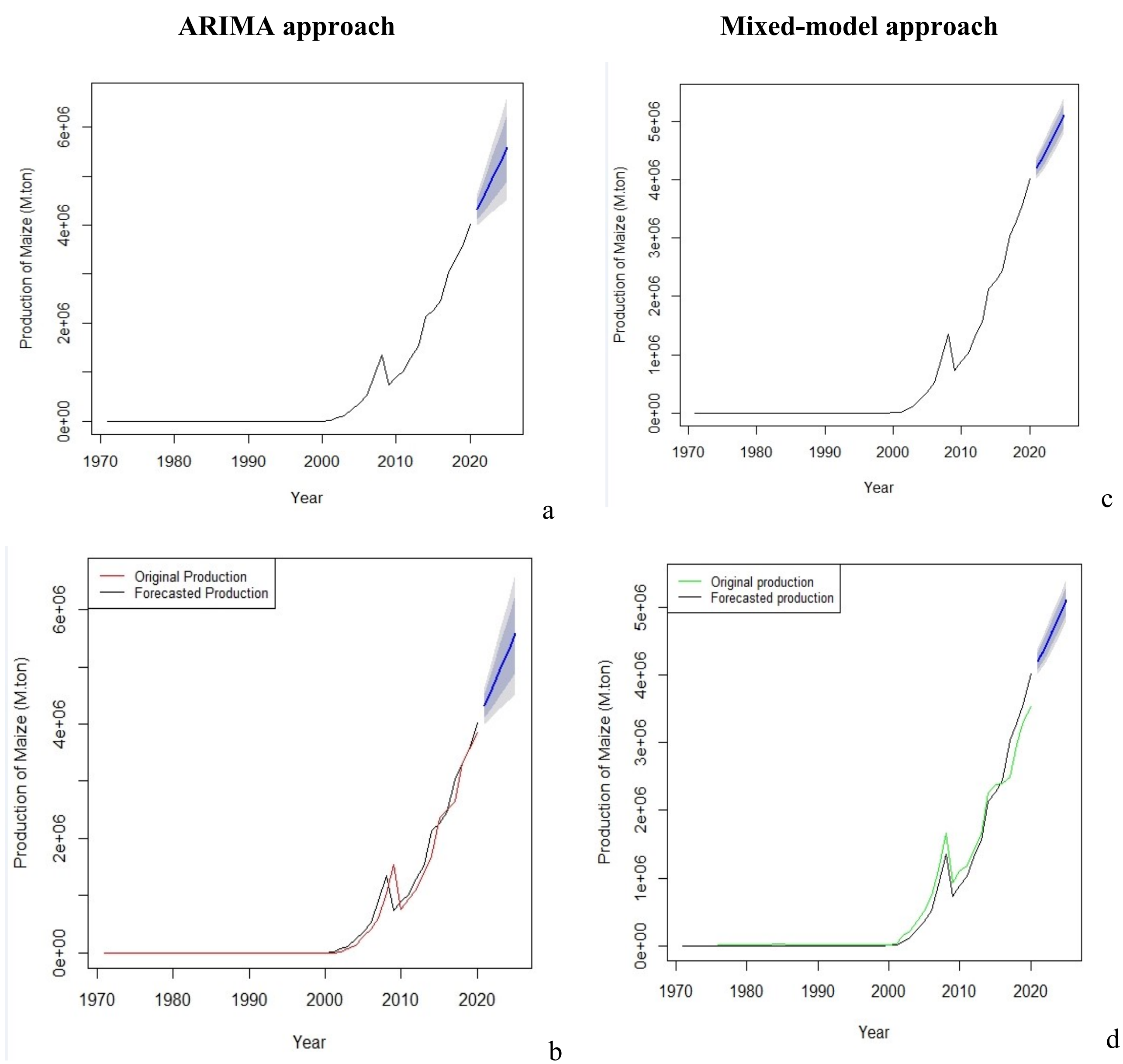

Figure 5: Predicted and actual values of maize production comparison. (a+b). ARIMA model; (c+d). Mixed-model

IV. CONCLUSION

Maize being an important cereal cop, has gained much interest and the production and area under cultivation are increasing day by day. Furthermore, maize is thought to have significant contribution in combating food insecurity in Bangladesh. Given the price volatility in local and international markets systematic planning for maize cultivation is necessary in the country. To make maize cultivation sustainable and efficient correct and timely information on the production is very important. This is very necessary in regards to storage, and import and export decisions, and any other incentives plans for the farmers. This study, using time series data, tried to predict the maize production through Box-Jenkins methodology in Bangladesh. The most appropriate Box-Jenkins ARIMA model is ARIMA (0, 2, 1) for forecasting the maize production all over Bangladesh. When area of maize is considered in the analysis the mixed-model is the best model rather than univariate ARIMA model. For both the models, forecast have been made for the period 2020-21 to 2024-25, where the mixed model shows the narrower range of confidence interval. Planners, academics, and smallholders in Bangladesh should use the proposed model to predict information and resource planning while making decisions about producing maize. Considering the availability of area information both ARIMA (before or during plantation) and mixed model (just before harvesting) may be useful. As maize is being considered for dual use, e.g., food and feed, proper planning and accurate prediction will guide the country to achieve the most in terms of food security. The specific policy recommendation is that forecasting of the maize production should be made immediately after plantation when area information will be available to facilitate decisions regarding import, export and storage management.

REFERENCES

Akpan, E. A., and Moffat, I. U. (2016). Dynamic Time Series Regression: A Panacea for Spurious Correlations. *International Journal of Scientific and Research Publications*, Volume 6, Issue 10, October 2016. ISSN 2250-3153.

AMIS. (2017). Chapter VI. Model based forecasting. *Strengthening Agriculture Market Information System (AMIS) in Bangladesh project*. Analytical report on methodologies of crop estimation and forecast and private stock of food grain survey 2016-17. Statistics and Informatics Division (SID), Bangladesh Bureau of Statistics (BBS). Ministry of Planning. 2017, 38-59.

BBS (2020). *Yearbook of Agricultural Statistics of Bangladesh*. Bangladesh Bureau of Statistics, Ministry of Planning, Government of the People's Republic of Bangladesh, Dhaka.

Biswas, R and Bhattacharyya, B. (2013). ARIMA modeling to forecast area and production of rice in West Bengal. *Journal of Crop and Weed*, 9(2):26-31.

Cressie, N. (1988). A Graphical Procedure for Determining Non-stationary in Time Series.

JASA. [83: 1108-15].

Hasan, M. N., Mohayem, M. A. Miah, Islam, M. S., Islam, Q. M. and Hossain, M.I. (2008). Change and Instability in area and production of Wheat and Maize in Bangladesh. *Bangladesh J. Agril. Res*.**33**:409-17.

Hossain, M. M., Abdullah, F. and Hossain, Z. (2017). Comparison of ARIMA and Neural Network Model to Forecast the Jute Production in Bangladesh. Jahangirnagar University Journal of Science (JUJS) Vol. 40, No. 1, pp.11-18.

Kumar,K. S. and Shitap, M. (2020). Statistical evaluation of stepwise regression method and autoregressive integrated moving average method for forecasting of groundnut (arachis hypogaea l.) productivity in Junagadh district of Gujarat. *Int.J.Curr.Microbiol. App.Sci*9(11):84-93 https://doi.org/10.20546/ijcmas.2020.911.009.

Kumari, P., Mishra, G. C., Pant, A. K., Shukla, G. and Kujur, S. N. (2014). Autoregressive Integrated Moving Average (ARIMA) approach for prediction of rice (*Oryza sativa* L) yield in India. *The Bioscan*, 9(3): 1063-1066.

Ljung, G. M and Box, G. E. P. (1978). On a Measure of Lack of fit in Time Series Models. *Biometrika*, 65: 297-303.

Makridakis, S., Wheelwright, S. C., Wiley & Sons, R. J. (1998). *A review of: "Forecasting: Methods and Applications"*. pp. 642. Third edition, ISBN 0-471-53233-9." IIE TRANSACTIONS, 31(3), p. 282.

Mishra, G. C. and Singh, A. (2013). A study on forecasting, prices of groundnut oil in Delhi by ARIMA methodology and Artificial Neural Networks. *AGRIS online papers in Economics and Informatics,* 5: 25-34.

Monlruzzaman.; Rahman, M. S.; Karim, M. K. and Alam, Q. M. (2009).Agro-Economic Analysis Of Maize Production In Bangladesh: A Farm Level Study. *Bangladesh J. Agril. Res.* 34(1): 15-24, March 2009.

Muhammed, F., Siddique, M., Bashir, M., and Ahamed, S. (1992). Forecasting rice production in Pakistan Using ARIMA models. *J. Animal Plant Sci.,* 2: 27-31.

Najeeb, I., Khuda, B. Asif, M. and Abid, S. A. (2005). Use of ARIMA Model for Forecasting Wheat Area and Production in Pakistan. *Journal of Agricultural and Social Sciences*, 1(2): 120- 122

Naveena, K., Rathod, S., Shukla, G. and Yogish, K. J. (2014). Forecasting of coconut production in India: A suitable time series model. *International Journal of Agricultural Engineering*, 7(1): 190–193. 162

Pankratz, A. (1991). *Forecasting with dynamic regression models.Forecasting with Dynamic Regressions Models*, 3nd Ed., New York, John Wiley and Sons, 1991DOI: 10.1016/0169-2070(92)90081

Paswan, S., Paul, A., Paul, A., and Noel, A. N. (2022). Time series prediction for sugarcane production in Bihar using ARIMA & ANN model. The Pharma Innovation Journal 2022; SP-11(4): 1947-1956.

Rachana, W., Suvarna, M. and Sonal, G. (2010). Use of ARIMA models for forecasting pigeon pea production in India. *Int. Rev. Bus. Finance*, 2(1): 97-107.

Rahman, N. A. F. (2010). Forecasting of boro rice production in Bangladesh: An ARIMA approach. *J. BangladeshAgril. Univ*. 8(1): 103–112.

Rahman, N. A. F., Aziz, M. A., Rahman M. M. and N. Mohammad. (2013). Modeling on Grass Pea and Mung Bean Pulse Production in Bangladesh Using ARIMA Model.*IOSR Journal of Agriculture and Veterinary Science (IOSR-JAVS)*

Rathod, S. and Mishra, G. C. (2018). Statistical Models for Forecasting Mango and Banana Yield of Karnataka, India. *J. Agr. Sci. Tech*. (2018) Vol.20: 803-816.

Sarda, C and Prajneshu. (2002). Modeling and Forecasting Country's Pesticide/ Consumption Data using ARIMA Time Series Approach. *Annals of Agricultural Research*, 23(4): 719-722.

Sarika, Iquebal, M. A. and Chattopadhyay, C. (2011). Modelling and forecasting of pigeonpea (*Cajanus cajan*) production using autoregressive integrated moving average methodology. *Ind. J. Agric. Sci.*, 81(6): 520-523.

Shabur, S. A. and Haque, M. E. (1993). Analysis of rice in Mymensing town market pattern and forecasting. *Bangladesh J. Agric. Econ*., 16: 130-133.

Sohail, A., Sarwar, A., and Kamran, M. (1994). Forecasting total Food grains in Pakistan. *J. Eng. Appl. Sci*., 13: 140-146.

Theil, H. (1961), Economic Forecasts and Policy, 2nd Edition, North-Holland, Amsterdam.

Uddin, M. A.; Rahman, K.S.; Rahman, M. M.; Mohammad, N. and Islam, A.F.M.T. (2015). Development of union level digital databases and maps of maize growing areas at Pirgonj in Thakurgaon district. *Bangladesh J. Agril. Res*. 40(4): 693-702.