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Transfer Function Approach to Modeling Rice Production in Bangladesh

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Abstract:

In Bangladesh the price of rice might be affected by many factors such as the less production in any year or the more production in any other year, lack of proper market systems, the propensity to hoard in order to make huge profits by businessman, and the lack of proper plan of government to procure the rice needed to meet the domestic demand from other countries. In advance it is required to know how much production is needed and how much production will grow in our country in order to manage the rice market properly. From a detailed analysis of numerical results, it can be concluded that the quality of prediction using alternative technique is generally superior to the quality of procedure such as standard time series techniques (ARMA, ARIMA etc). The limitations of the time series techniques mentioned above suffers are attributed to not to consider the other inputs which influence the rice production. Thus, the transfer function technique is assessed using different native techniques. Transfer functions (TF) are frequently used to characterize the input-output relationships. In this study we consider the output series along with

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one important input variable cultivated area to model the boro production. To model the two time series variables transfer function-noise model is considered. Among three tentative models considered to be fitted to data, the model 2 is $Y_t = \frac{(\omega_0 - \omega_1 B)}{(1-\delta_1 B)} X_t$ *found to be statistically significant.*

Key words: Rice production, Bangladesh, Transfer function, ARIMA modeling

Introduction:

Production of rice depends on some measures which are taken during cultivation. In case of both local and cultivated varieties weathering of soil, tillage, irrigation, fertilizer application are maintained so that the production may not affected by any unexpected event. But now a day we are keeping our concentration to the high yielding varieties evolved by the research organizations like BRRI, BINA, BARI etc. have produced many high yielding and disease resistant varieties. Scientists have changed the genetic sequence of the improved rice varieties. Production inefficiency is usually analyzed by its two components– technical efficiency and allocative efficiency. In this study we provide a direct measure of production efficiency of the Bangladeshi rice farmers using a stochastic profit frontier and inefficiency effects model.

Source of data

Data is collected from Ministry of Agriculture and Bangladesh Bureau of Statistics. The variables of interest include boro production from 1970 to 2008 and the corresponding cultivated area of the same time length.

Transfer Function Modelling

Single input transfer function-noise models

We begin our discussion by considering the situation in which an output or, to use terminology more familiar to economists, endogenous variable Y_t is related to a single input, or exogenous, variable X through the dynamic model

$$Y_t = \upsilon(B)X_t + N_\upsilon \qquad (1.1)$$

where, the lag polynomial $\upsilon(B) = \upsilon_0 + \upsilon_1 B + \upsilon_2 B^2 + \ldots,$ allows X to influence y via a distribution lag, $\upsilon(B)$ often being referred to as the transfer function and the coefficients υ_i as the impulse response weights. The relationship between Y and X will not be deterministic; rather, it will be contaminated by noise, this being captured by the stochastic process N_t, which will generally be serially correlated. The crucial assumption made in the transfer function-noise model (7.2.1) is that X_t and N_t are independent, so that past X's influence future Y's, but not vice-versa. The full implications of this assumption, which rules out feedback from Y to X, along with other related concepts of exogeneity.

In general $\upsilon(B)$ is of infinite order, and hence some restrictions must be placed on the transfer function before empirical implementation becomes feasible. The typical way in which restrictions are imposed is analogous to the approximation of the liner filter representation of a stochastic process by a ratio of low order polynomials in B, which leads to the familiar ARMA model (see Chapter 4). In the present circumstances, $\upsilon(B)$ is written as the rational distribution lag

$$\upsilon(B) = \frac{\omega(B)B^b}{\delta(B)} \qquad (1.2)$$

Here, the numerator and denominator polynomials are defined as

$$\omega\left(B\right)=\omega_0-\omega_1B-...-\omega_sB^s$$

and

$$\delta\left(B\right)=1-\delta_1B-...-\delta_rB^r$$

with the roots of $\delta(B)$ all assumed to be less than unity. The possibility that there may be a delay of b periods before X begins to influence Y is contemporaneous relationship, b = 0. The parameter b is sometimes referred to as the dead-time of the model. The relation between the impulse response weights υ_i and the parameters $\omega_0,...,\omega_i,\delta_1,...,\delta_r$ and b can be obtained by equating the coefficients of B^j in

$$\delta(B)\upsilon(B)=\omega(B)B^b$$

Model Identification and Validation

Stationarity Check

The prediction of rice production in Bangladesh correctly is required for not only ensuring the food supply by government's different activities such as import but also curbing the price of rice through interventions because rice market in Bangladesh is very volatile. The production of rice is affected by climatic volatility, shortage of logistic supports, such as fertilizer, seeds, irrigation, etc, low and high price of rice influenced mostly by lack of proper management of uninterrupted rice supply by government. The prediction of rice production requires sophisticated techniques such as transfer function model.

This section presents the model identification, estimation, and validation approaches. The techniques include line diagrams, correlogram, unit root test, cross correlations, Transfer function modeling and forecast of time series data. Here our main objective is to find the mechanism of generating time series rice production over time using transfer function, a function which utilizes the relationship among different time series data, one being treated as dependent variable and others independent. To model the rice production over time a noise model and transfer function contributed by one important input variable area cultivated are considered here. The verification of association between two variables considered for model building is confirmed through a line diagram which shows a positive relationship between them.

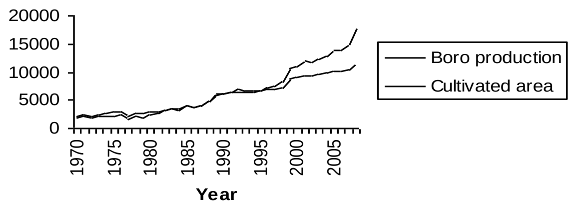

Figure 01: Line graph of Boro rice production and its cultivated area.

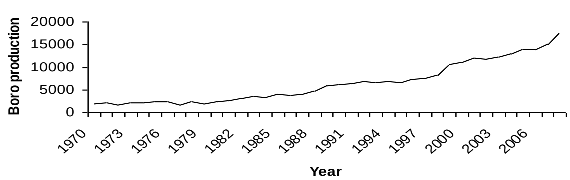

Figure 02: Boro production in Bangladesh from 1970-2008

Figure 1 shows that the Boro production from 1970 to 2008 the overall Boro production over time is increasing. That is, the upward trend in the level of Boro production reinforces. To model data requires some transformation such as differencing in order to make the non- stationary data into stationary.

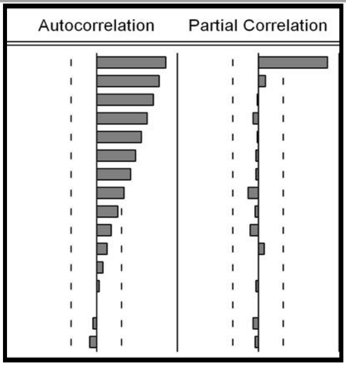

Figure 03: Autocorrelation and partial autocorrelation function plot for Boro rice production

To confirm that the level in Boro production is not constant, we can generate ACF and PACF plots. ACF charts plot the average correlation between any time point and the previous point. The PACF plots the same relation with intervening points correlations removed.

ADF Test Statistic	1.703222	1% Critical Value*	-3.6353
		5% Critical Value	-2.9499
		10% Critical Value	-2.6133

Table 01: Unit root test for variable Boro production

Review of these plots reveals extensive auto correlation. The autocorrelation, statistically significant, declines exponentially, confirming the non-stationarity of data. With the help ADF test we may conclude that the production data is non-stationary. Because the value of ADF tests statistics is less than the tabulated value. Since the rice production over time is non-stationary, to model this series data stationarity of data is required. The way of making non-stationary data into stationary is difference approach. So first difference of the data is made and verified the stationarity again by the approaches used below.

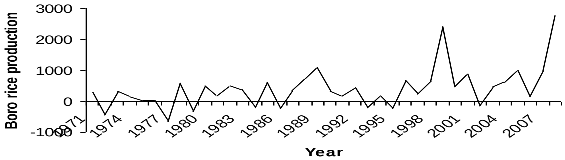

Figure 04: Line graph of boro production after first difference

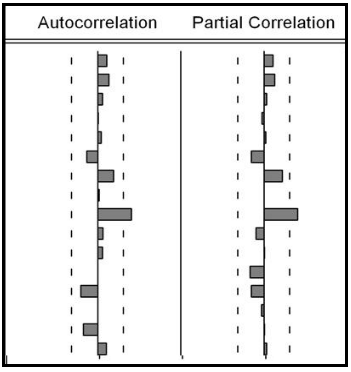

Figure 05: Autocorrelation and partial autocorrelation function plot for rice production after first difference

ADF Test Statistic	-3.291955	1% Critical Value*	-4.2324
		5% Critical Value	-3.5386
		10% Critical Value	-3.3009

Table 02: Unit root test for variable Boro production after first difference

The line diagram and sample ACF and SPACF confirm that the first differenced rice production data is stationary. The formal test for verifying the non-constant level in the data has been recourse, which is ADF test. The results of ADF applied to the transformed data are presented in table (02). The conformity of stationarity of data is established in the above three approaches.

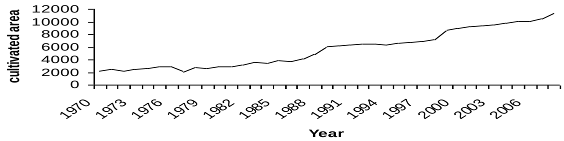

Figure 06: Cultivated area of Boro in Bangladesh from 1970-2008

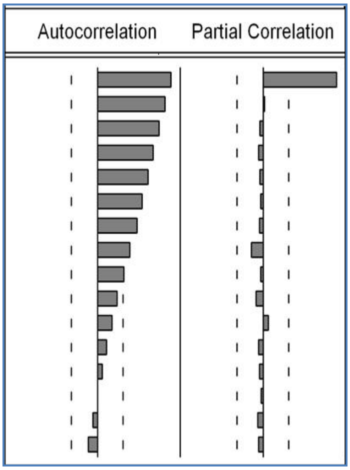

Figure 07: **Autocorrelation and partial autocorrelation function plot for Cultivated Boro area.**

Figure 06 shows the area cultivated with Boro production from 1970 to 2008. The overall Boro production area over time is increasing. In the line graph we see that the area data is non stationary because it has a trend. If we convert the non stationary data into stationary data, then we will be able to apply the various stationary methods such as ARMA, ARIMA etc. That is, the upward trend in the level of Boro cultivated area has a next of kin .we can produce ACF and PACF plots for the area data. ACF charts plot the association between several time positions and the previous position. The PACF plots the similar relation with intervening points correlations detached.

ADF Test Statistic	1.20914	1% Critical Value*	-3.6117
		5% Critical Value	-2.9399
		10% Critical Value	-2.6080

Table 03: Unit root test for variable Boro cultivated area

The ACF and PACF show the data is non-stationary. The autocorrelations decline exponentially as the lag goes far away. A more formal test like the Augmented Dickey Fuller (ADF) test which confirms the time series data is whether stationary or not. With the help ADF test we may conclude that the cultivated area data is non stationary because the absolute value of ADF tests statistics 1.209194 is less than the absolute tabulated value of that statistic.

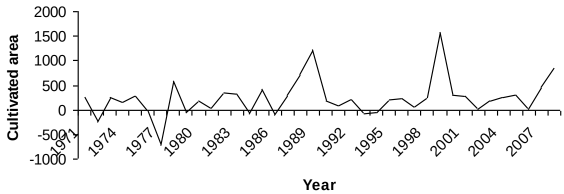

Figure 08: Line graph of Boro cultivated area after first difference

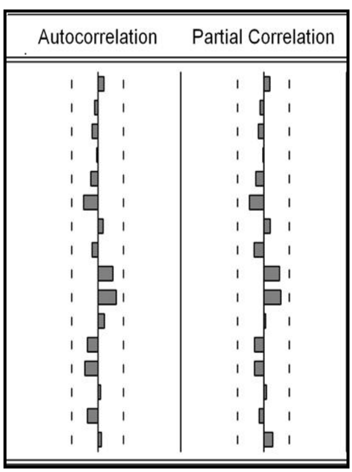

Figure 09: Autocorrelation and partial autocorrelation function plot for Boro area after first difference

Figure 09 shows the area cultivated after first difference from 1970 to 2008. The overall Boro cultured area, seems to be constant over time.

ADF Test Statistic	-5.258241	1% Critical Value*	-3.6171
		5% Critical Value	-2.9422
		10% Critical Value	-2.6092

Table 04: Unit root test after performing first difference

With the help ADF test we may bring to a close that the cultivated area data after first difference is stationary. Because the absolute value of ADF test statistics is greater than the absolute tabulated value. So, we can say that the time series data for cultivated area is stationary after first difference.

Model identification

The first step is to identifying the transfer function is to prewhitten the input series. The line diagram of land cultivated with rice , the plot of ACF and PACF as shown in section of stationarity check indicate that the input series area, X_t is not stationary but first difference is stationary. This series X_t is modeled as an ARIMA (0, 1, 0). The model is $X_t - X_{t-1} = \alpha_t$.

We now pretreat output series Y_t as like as the prewhitened input series X_t. The model is $Y_t - Y_{t-1} = \beta_t$.Now we calculate cross-correlation between α_t and β_t to identify transfer function identification parameters r, s and b.

Where, r = Autoregressive order of function.
s = Number of moving average terms-1
b = Delay of impact

Lag	Covariance	Correlation
-9	375960	0.19992
-8	357993	0.19036
-7	453681	0.24125
-6	358922	0.19086

-5	426298	0.22668
-4	480318	0.25541
-3	599419	0.31874
-2	573277	0.30484
-1	665895	0.35409
0	1011784	0.53802
1	788056	
2	687166	0.36540
3	657400	0.34957
4	640870	0.34078
5	601583	0.31989
6	564310	0.30007
7	490870	0.26102
8	461043	0.24516
9	376210	0.20005

Table 05: Cross correlation between Boro production and cultivated area

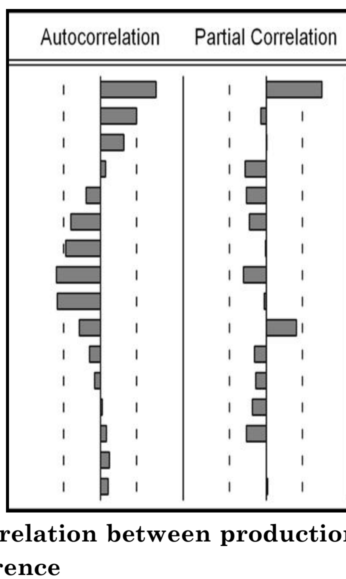

Figure 10: Cross correlation between production and land cultivated area after first difference

At first, first significant CCF (k) is found at the point $b = 0$. Then the significant CCF (k) is found at the point -1 and -2. So, the value of $s = (b + s) - b = 2$

To find out the impulse function, at first we have to calculate cross-correlation, variance of prewhitened inputs series, α_t and pretreated output series, β_t. The impulse function is given by

$$\hat{v}_k = \left(\frac{\hat{\sigma}_\beta}{\hat{\sigma}_\alpha}\right)\hat{\rho}_{\alpha\beta}(K)$$

Lag	Cross correlation ($\hat{\rho}_{\alpha\beta}(K)$)	Input	Output	Impulse function ($\hat{v}_k$)
0	0.8415	The standard deviation of prewhitened input series is $\hat{\sigma}_\alpha = 387.9985$	The standard deviation of pretreated output series is $\hat{\sigma}_\beta = 387.9985$	1.443132
1	0.0907			0.155546
2	0.0448			0.07683
3	0.0067			0.01149
4	-0.0469			-0.08043
5	-0.0105			-0.01801
6	-0.1565			-0.26839
7	0.1126			0.193104
8	-0.0128			-0.02195
9	0.1929			0.330814
10	0.0603			0.103412
11	0.0428			0.0734
12	-0.0805			-0.13805
13	-0.1857			-0.31847
14	-0.0049			-0.0084
15	-0.127			-0.2178
16	0.0051			0.008746

Table 06: Finding impulse function against lag value

Now, the value of r is determined from the graph

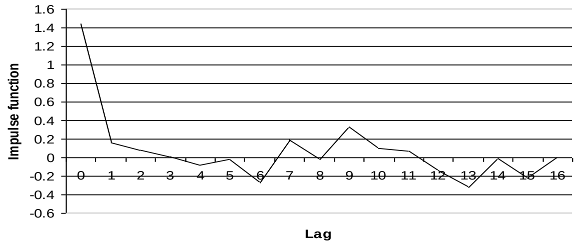

Figure 11: Line graph of lag value and impulse function

From the graph we see that the curve holds a damped sign and an exponential decay. So, the value of r may be 1 or 2.The identification of r, b, and s leads to consider three tentative models. The model specifications are as follows:

Model 1: $Y_t = (\omega_0 - \omega_1)X_t$

Model 2: $Y_t = \dfrac{(\omega_0 - \omega_1 B)}{(1-\delta_1 B)} X_t$

Model 3: $Y_t = \dfrac{(\omega_0 - \omega_1 B)}{(1-\delta_1 B - \delta_2 B^2)} X_t$

Model estimation

Now we estimate three model separately. The results of estimated models are presented in the following tables.

Now, we have to choose a correct to explain the boro production time series data in terms of noise model and transfer model among three tentative models.

coefficient	Estimate	Std. error	t-stat	Significant	AIC	BIC
θ_0	66.83	80.2773	0.83	0.4109	546.39	551.229
ω_0	1.44	0.1592	9.06	<0.001		
ω_1	-.02016	0.1654	-0.12	.9036		

Table 07: Estimation of model 1

Coefficient	Estimate	Std. error	t-Stat	Significance	AIC	SBC
θ_0	-1195.7	2350.3	-0.51	0.6143	542.19	548.63
ω_0	1.49132	0.15966	9.34	<0.0001		
ω_1	1.23904	0.19394	6.39	<0.0001		
δ_1	0.9651	0.05515	17.50	<0.0001		

Table 08: Estimation of Model 2

Coefficient	Estimate	Std. error	t-Stat	Significance	AIC	SBC
θ_0	31.673	111.095	0.29	0.7775	535.37	543.29
ω_0	1.434	0.168	8.54	<0.001		
ω_1	0.045	1.47	0.003	0.975		
δ_1	0.041	1.013	0.04	0.967		
δ_2	0.1153	0.118	0.07	0.333		

Table 09: Estimated Model 3

Among the three models, the model 1 has the highest value of AIC and SBC & all the coefficient term are insignificant. So, Model 1 is less efficient.

Again, the model 3 has lower value of AIC and SBC but all the coefficient terms are insignificant. On the other hand, the model of has slightly higher value of AIC and SBC but all the value of coefficients terms are significant. So, the model 2 is the correct tentative model.

The coefficient of tentative model can be interpreted in the following way.

The moving average constant part of the ARIMA model for the noise series is $\omega_0 = -1195.69$.

The numerator factor of a transfer function is like the moving average part of the ARIMA model and its value is $\omega_1 = 1.23904$

The denominator factor of a transfer function is like autoregressive part of the ARIMA model and its value is $\delta_1 = 0.96501$.

Diagnostic check

After the model coefficient has been estimated, various checks may be performed to determine its adequacy. The fitted model can be inadequate if the fitted model, the transfer function, or both the noise and transfer function models are incorrect.

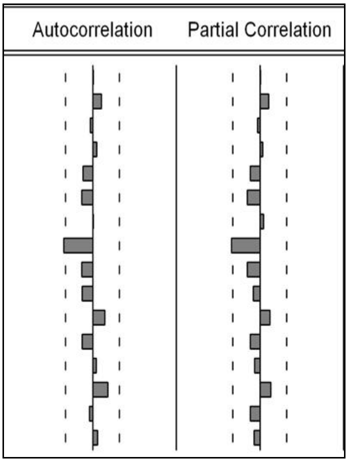

Figure 12: Autocorrelation and partial autocorrelation function of residuals

All auto correlation and partial auto correlation lie between 95% confidence interval. Thus, the model specification is correct.

To lag	χ^2	DF	$\Pr > \chi^2$	Autocorrelations					
6	2.37	6	0.8823	0.030	0.017	0.083	0.046	-0.084	-0.187
12	6.81	12	0.8698	0.065	-0.257	-0.057	0.009	0.118	-0.014
18	10.04	18	0.9305	-0.104	0.164	0.063	0.036	0.061	-0.06
24	14.33	24	0.9387	-0.024	-.024	0.037	-0.052	0.019	0.014

Table 10: Auto correlation check for residuals

The χ^2 test statistics indicates for the residuals are uncorrelated (white noise) or contain additional information that might be utilized by a more complex model. In this case, the test statistics reject that autocorrelation exists at the level of significance. That is, the residuals are white noise.

Forecasting

There is an insightful relationship between forecasting and the rice production. In production as in forecasting, one casts a 'year' forward. This cast is called a forward cast or forecast.

There are mainly three types of forecasting method such as Time series (Univariate), Causal (Multivariate) and Qualitative forecasting Methods. For Boro production and cultivated area data we have applied Causal (Multivariate) forecasting method. After first difference, the boro production and cultivated area time series data have become stationary after performing first difference. Thus, the time series data for Boro production and its area, the simplest from of the transfer function can be written as,

$$Boro - B(Boro) = \frac{\omega_0(Area) - \omega_0 \times B(Area)}{1 - \delta_1 B}$$

After some simplification, we can perform the relationship between future boro production with the value present and past value of boro production and cultivated area. The aspect relationship has indicated as follows:

$$Boro = (\delta_1 + 1)B(Boro) + \delta_1 B^2(Boro) + \omega_0(Area) - \omega_0 B(Area)$$

We are able to perform in forecast, such as:

$$Boro(2008) = 14869.75$$

Conclusion

We have considered three tentative models. Among these three tentative models, we have chosen a correct model for this data. We have estimated three model coefficient and AIC& SBC criteria. By comparing, the model coefficient and AIC & SBC criteria we have decided that the Model 2 is correct for the production and area data. The diagnostic checking is performed .we have forecasted for the year 2008. But future forecast is not possible because input variables such as how much land will be cultivated are not possible to know. If the input variable such as cultivated area for the future year is measured, then we can forecast the rice production for the future year. From a detailed analysis of numerical results, it can be concluded that the quality of prediction using alternative technique is generally superior to the quality of procedure such as standard time series modes (ARIMA). Thus, the transfer function technique is assessed using different native techniques.

Rice production plays a vital role in Bangladesh. It is very useful to forecast the rice production for future year. If the proper forecast is available then the government should take proper decision to improve rice production. Whether the rice will be imported or not depends on proper prediction when the production of rice is sufficient, the government takes necessary steps to procure additional rice to stabilize the price level. If we can predict the production of rice more accurately, it will be more helpful for our policy makers to take necessary steps to stabilize the price of rice using the advance knowledge of rice production.

Acknowledgements

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