Research Article

# Forecasting Production and Yield of Sugarcane and Cotton Crops of Pakistan for 2013-2030

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**Abstract** | This study attempts to forecast production and yield of two main cash crops namely sugarcane and cotton crops of Pakistan by using Auto Regressive Moving Average (ARMA) and Auto Regressive Integrated Moving Average (ARIMA) models of forecasting. Using data for 1948 to 2012, productions and yields of both crops were forecasted for 18 years starting from 2013 to 2030. ARMA (1, 4), ARMA (1, 1) and ARMA (0, 1) were found appropriate for sugarcane production, sugarcane yield, and cotton production respectively, whereas ARIMA (2, 1, 1) was the suitable model for forecasting cotton yield. Some diagnostic tests were also performed on fitted models and were found well fitted.

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**Keywords** | Forecast, Sugarcane, Cotton, Production, Yield, ARIMA

## Introduction

Sugarcane and cotton are the two major cash crops sown in Pakistan. Punjab, Sindh and Khyber Pakhtunkhwa are the major sugarcane producing provinces of the country. Total area under sugarcane crop during 2010-11 was 987.6 thousand hectares in the country. Punjab is the largest province in terms of area under sugarcane which accounts for more than 68 percent of the total area under sugarcane followed by Sindh (22.9 %) and Khyber Pakhtunkhwa (8.9 %) (GOP, 2012). However, Sindh produces highest yield (60.8 tonnes per hectare) followed by Punjab (55.8 tonnes per hectare) and Khyber Pakhtunkhwa (45.6 tonnes per hectare). Its production has increased by almost 27 percent from 43.6 million tonnes in 2000-01 to 55.3 million tonnes in 2010-11. It is primarily grown for sugar production in the country, however, other products like bio fuel, chipboard, organic fertilizer, paper, and fiber etc can also be produced from sugarcane. Its share in total value added of agriculture is approximately 3.7% (GOP, 2012).

Cotton is mainly grown in Punjab and Sindh provinces. This crop contributes significantly in Pakistan economy by providing raw material to textile industry as well as foreign exchange earnings through export of cotton lint (GOP, 2012). Its share in agriculture value added is 8.6 percent and also accounts for 1.8 percent to national GDP. During 2010-11, total area under cotton crop was 2.69 million hectares in the country. Punjab accounts for more than four-fifth of the total area under cotton in the country. In terms of yield, Sindh contributes 1354 kg/hectare whereas; cotton yield in Punjab was only 607 kg/hectare during 2010-11. Area under cotton has increased from 2.2 million in 1980-81 to 2.7 million hectares in 2010-11 (GOP, 2012).

Being two major cash crops and contributing significantly in the agricultural economy of the country, it is worthwhile to know about the production and yield status of these crops in future. If past values of crop production and yield are given, one can use past pattern of the data to forecast crop production and yield by employing forecasting model. Various models have been developed to forecast future values; however, in uni-variate time series analysis, ARIMA model technique has been used extensively in the literature for forecasting purpose. Efforts have been made to forecast production and productivity of sugarcane employing ARIMA models (Yaseen et al., 2005; Bajpai and Venugopalan, 1996). Other attempts using ARIMA models include forecasting of sugarcane production in Pakistan (Muhammad et al., 1992), forecasting of area, production and productivity of different crops for Tamilnadu State (Balanagammel et al., 2000), forecasting wheat production in Canada and Pakistan (Boken, 2000; Saeed et al., 2000), forecasting fish catches (Tsitsika et al., 2007; Venugopalan and Srinath, 1998), forecasting agricultural production at state level (Indira and Datta, 2003), forecasting sugarcane area and yield for Pakistan (Masood and Javed, 2004), forecasting production of oilseeds (Chandran and Prajneshu, 2005), forecasting and modeling of wheat yield in Pakistan (Ullah et al., 2010), sugarcane yield forecasting for Tamilnadu (Suresh and Krishnaprya, 2011), and forecasting productivity in India (Padhan, 2012).

This paper focuses on Autoregressive Integrated Moving Average (ARIMA) model for forecasting production and yield estimates of sugarcane and cotton. The rest of paper is organized as follows. Section 2 describes data and methodology. Section 3 discusses results and discussions while, conclusion has been made in section 4.

## Data and Methodology

This study is based on secondary data of cash crops for forecasting production and yield of sugarcane and cotton crops. The production and yield data for sugarcane and cotton have been taken from various issues of Economic Survey of Pakistan (GOP, Various issues), and Agricultural Statistics of Pakistan (GOP, 2007). The study covers data from 1948 to 2012. Average annual growth rate of production and yield for sugarcane and cotton crops are reported in table 1.

Various models have been used in the literature to forecast time series data; however, Auto Regressive Integrated Moving Average (ARIMA) technique is used by this study to forecast production and yield of sugarcane and cotton for Pakistan. It is the most general form of stochastic models for analyzing time series data. The ARIMA models include autoregressive (AR) terms, moving average (MA) terms, and differencing (or integrated) operations. The model is called AR model if it contains only the autoregressive terms. Model is known as MA model if it involves only the moving average terms. It is known as ARMA models when both autoregressive and moving average terms are involved. Finally when a non-stationary series is made stationary by differencing method, it is known as ARIMA model. The general form of ARIMA is denoted by ARIMA (p,d,q), where 'p' represents the order of autoregressive process, 'q' represents the order of moving average process, while 'd' shows the order of differencing the series to make it stationary.

**Table 1:** *Decade-wise Average annual growth rate of Production and Yield for Sugarcane and Cotton crops in Pakistan*

| Decade | Sugarcane | | Cotton | |
|---|---|---|---|---|
| | Production | Yield | Production | Yield |
| 1971-80 | 4.01 | 0.31 | -1.58 | -2.14 |
| 1981-90 | 0.26 | 1.03 | 10.27 | 7.78 |
| 1991-00 | 3.75 | 1.43 | 0.14 | -1.02 |
| 2001-10 | 1.48 | 1.22 | 2.26 | 2.06 |

The general form of AR process of order p, denoted by AR (p) is written as follows:

$$Y_t = \Theta + \delta_1 Y_{t-1} + \ldots + \delta_p Y_{t-p} + \varepsilon_t \ldots\ldots (1)$$

Where, $Y_t$ is thedependant variable at time t, $Y_{t-1}$…… $Y_{t-p}$ are explanatory variables at time lags t-1, … t-p, $\varepsilon_t$ is the error term at time t.

The general form of MA process of order q is given as follows:

$$Y_t = \varepsilon_t - \gamma_1 \varepsilon_{t-1} - \gamma_2 \varepsilon_{t-2} - \ldots - \gamma_q \varepsilon_{t-q} \ldots\ldots (2)$$

Where $\varepsilon_{t-1}$, $\varepsilon_{t-2}$ … $\varepsilon_{t-q}$ are the forecast errors at time t-1, t-2 … t-q respectively. $\gamma_1$…. $\gamma_q$ are the coefficients to be estimated by OLS. The forecast errors represent the effects of the variable which is not explained by the model.

Finally, the general form of the ARIMA (p,d,q) can be written as follows:

$$\Delta^d Y_t = \Theta + \delta_1 \Delta^d Y_{t-1} + \delta_2 \Delta^d Y_{t-2} + \ldots + \delta_p \Delta^d Y_{t-p} + \varepsilon_t - \gamma_1 \varepsilon_{t-1} - \gamma_2 \varepsilon_{t-2} - \ldots - \gamma_q \varepsilon_{t-q} \ldots\ldots\ldots (3)$$

**Table 2:** *Results of Unit Root Test(Augmented Dickey-Fuller Test: ADF)*

| Variables | Intercept / Intercept & Trend | Level | First difference | Order of Integration |
|---|---|---|---|---|
| S_P | Intercept & Trend | -3.70** | - | I(0) |
| S_Y | Intercept & Trend | -3.77** | - | I(0) |
| C_P | Intercept & Trend | -2.09 | -9.73*** | I(1) |
| C_Y | Intercept & Trend | -4.20*** | - | I(0) |

***** indicate the rejection of null hypothesis of unit-root at 1% level of significance. ** indicate the rejection of null hypothesis of unit-root at 5% level of significance. The variable (S_P), (S_Y), (C_P) and (C_Y) represents sugar production, sugar yield, cotton production and cotton yield, respectively. ♣As both Intercept and Trend were significant, therefore, both were used in ADF test instead of using Intercept only.*

Where, $\Delta d$ represents differencing of order d, i.e., $\Delta Y_t = Y_t - Y_{t-1}$, $\Delta Y_t = \Delta Y_t - \Delta Y_{t-1}$ and so forth, $Y_{t-1}$ …… $Y_{t-p}$ show lags of the variable,indicates constant term of the modeland $\delta_1$…. $\delta_p$ are parameters to be estimated-by using ordinary least square method (OLS).

In this study we follow Box-Jenkins (1976) procedure of ARIMA modeling i.e. identification, estimation, diagnostic checking, and forecasting time series data of sugarcane and cotton crops of Pakistan. The ARIMA modeling procedure starts with identification of the model, however, stationarity of variables of interest is also required. The stationarity can be tested both through graphics and through other formal techniques i.e. Partial Autocorrelation Function (PACF), Autocorrelation Function (ACF), and Augmented Dickey-Fuller test (ADF) of unit root. If the variables of interest are found non-stationary at level, the data need transformationin such a way to make them stationary. The model can be identified through PACF and ACF. After identification of the model, the next step is the estimation of model parameterswhich is done through Ordinary Least Square (OLS) method. Moving further, various diagnostic tests are used on residual of the model. If the model passes successfully through these diagnostics tests, then the estimated coefficients of forecasting can be used for future values.

## Results and Discussions

The results of unit root test for sugarcane and cotton crop production and yield are given in table 2. The results indicate that production and yield of sugarcane crop are stationary at level i.e. both series are integrated of order zero I (0). So it is not needed to make these series stationary by taking difference. Similarly, the yield series of sugarcane was stationary at level. On the other hand, production series of cotton crop is non-stationary at level and therefore, it was made stationary by taking first order differencing. Therefore, ARMA model was used for forecasting production and yield of sugarcane crop, yield of cotton crop, whereas, ARIMA model was employed to forecast production of cotton crop of Pakistan.

**Table 3:** *Estimates of Sugarcane Production Parameters*

| Type | Coefficients | S.E | t-statistic | Prob. |
|---|---|---|---|---|
| AR(1) | 0.979 | 0.028 | 34.884 | 0.0000 |
| MA(4) | 0.534 | 0.118 | 4.520 | 0.0000 |
| MA(2) | -0.443 | 0.113 | -3.922 | 0.0002 |

**Table 4:** *Estimates of Sugarcane Yield Parameters*

| Type | Coefficients | S.E | t-ratio | Prob. |
|---|---|---|---|---|
| AR(1) | 0.997 | 0.027 | 36.623 | 0.0000 |
| MA(1) | -0.477 | 0.123 | -3.868 | 0.0003 |

Using diverse values of p and q, a range of ARMA and ARIMA models have been fitted in order to choose appropriate models. Appropriate models were selected based on certain selection criterion, for example, Schwarz-Bayesian Information Criteria (SBC) and Akaike Information Criteria (AIC). Consequently, ARMA (1, 4) and ARMA (1, 1) were found appropriate for production and yield of sugarcane respectively. Similarly, ARMA (0, 1) was found appropriate for production of cotton crop. Finally, ARIMA (2, 1, 1) was the appropriate model to be used for forecasting cotton yield. The parameters estimates for sugarcane production and yield are given in table 3 and table 4 respectively along with their standard errors and t-ratios. Likewise, parameters estimates for cotton production and yield are given in table 5 and table 6 respectively.

Once the models were fitted and estimated, the next step in Box-Jenkins (1976) procedure was diagnostic

**Table 5:** *Estimates of Cotton Production Parameters*

| Type | Coefficients | S.E | t-statistic | Prob. |
|---|---|---|---|---|
| MA(1) | -0.486 | 0.113 | -4.284 | 0.0001 |

**Table 6:** *Estimates of Cotton Yield Parameters*

| Type | Coefficients | S.E | t-ratio | Prob. |
|---|---|---|---|---|
| AR(2) | -0.516 | 0.119 | -4.353 | 0.0001 |
| AR(1) | 1.515 | 0.117 | 12.953 | 0.0000 |
| MA(1) | -0.984 | 0.030 | -32.619 | 0.0000 |

checking of the fitted models. For this purpose, we used ACF and PACF of plotted residuals of the fitted models. The ACF and PACF of the plotted residuals of production and yield of both sugarcane and cotton crops were found within the limits which indicated that models were well fitted (see Appendix-C). Using parameter estimates of the fitted models, forecast for production and yield of sugarcane and cotton crops of Pakistan for the years 2013 to 2030 were estimated and presented in Appendix-A, whereas, the graphical presentation are given in Appendix-B.

The forecasted values of sugarcane crop reveal that it will reach 71,414 thousand tonnes and its yield will attain 60,765 kg/ha by 2030. On the other hand, the forecast of cotton production is 15,479 thousand tonnes and its yield is 870 kg/ha for 2030.

## Conclusions

One of the main objectives of this study was to forecast production and yield of sugarcane and cotton crops of Pakistan. Auto Regressive Moving Average (ARMA) and Auto Regressive Integrated Moving Average (ARIMA) models were used for this purpose. Time series data for 65 years (1948 to 2012) have been used in this study. All the essential steps of ARMA and ARIMA modeling have been systematically followed to forecast productions and yields of selected crops from 2013 onward to 2030. These forecast values could be used for formulating agriculture policy especially for sugarcane and cotton crops by policy makers at national level.These models use the historical time series data for forecasting, however, there could be some other factors affecting production and yield of these crops. For example, availability of high yielding varieties, applying best management practices, judicious use of pesticides etc. Consequently, the future thrust of this study is to apply other available models of forecasting which have features of incorporating more agriculture related information to forecast production and yields of these crops.

The study used univariate analysis for forecasting; however, this does not mean that the technique supersedes multivariate techniques. ARIMA does not perform well in case of volatile series. Moreover, ARIMA models of forecasting are 'backward looking' and do not perform better during forecasting at turning points.

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## APPENDIX-A

**A-I:** *Forecast of Sugarcane Production and Yield from 2013-2030 with 95% confidence interval*

| Year | Production (000 t) | | | Yield (kg/ha) | | |
|---|---|---|---|---|---|---|
| | Forecast | 95 % Limit | | Forecast | 95 % Limit | |
| | | Lower | Upper | | Lower | Upper |
| 2013 | 55859 | 50103 | 61615 | 54689 | 49575 | 59803 |
| 2014 | 58287 | 52531 | 64043 | 54874 | 49760 | 59988 |
| 2015 | 57927 | 52171 | 63683 | 55103 | 49990 | 60217 |
| 2016 | 58302 | 52546 | 64058 | 55370 | 50256 | 60484 |
| 2017 | 59865 | 54110 | 65621 | 55667 | 50553 | 60781 |
| 2018 | 61060 | 55305 | 66816 | 55989 | 50875 | 61103 |
| 2019 | 62073 | 56317 | 67829 | 56332 | 51218 | 61445 |
| 2020 | 62995 | 57239 | 68751 | 56691 | 51577 | 61805 |
| 2021 | 63872 | 58116 | 69628 | 57065 | 51951 | 62179 |
| 2022 | 64727 | 58971 | 70483 | 57450 | 52336 | 62564 |
| 2023 | 65571 | 59815 | 71327 | 57845 | 52731 | 62959 |
| 2024 | 66410 | 60654 | 72166 | 58247 | 53134 | 63361 |
| 2025 | 67246 | 61490 | 73001 | 58657 | 53543 | 63770 |
| 2026 | 68080 | 62324 | 73836 | 59071 | 53957 | 64185 |
| 2027 | 68914 | 63158 | 74670 | 59490 | 54376 | 64604 |
| 2028 | 69747 | 63992 | 75503 | 59912 | 54798 | 65026 |
| 2029 | 70581 | 64825 | 76337 | 60337 | 55223 | 65451 |
| 2030 | 71414 | 65658 | 77170 | 60765 | 55651 | 65879 |

*Source: Authors' estimation*

**A-2:** *Forecast of Cotton Production and Yield from 2013-2030 with 95% confidence Interval*

| Year | Production (000 b) | | | Yield (kg/ha) | | |
|---|---|---|---|---|---|---|
| | Forecast | 95 % Limit | | Forecast | 95 % Limit | |
| | | Lower | Upper | | Lower | Upper |
| 2013 | 12472 | 10301 | 14643 | 728 | 601 | 855 |
| 2014 | 12649 | 10478 | 14819 | 734 | 607 | 861 |
| 2015 | 12826 | 10655 | 14996 | 741 | 614 | 868 |
| 2016 | 13002 | 10832 | 15173 | 749 | 622 | 876 |
| 2017 | 13179 | 11008 | 15350 | 757 | 631 | 884 |
| 2018 | 13356 | 11185 | 15527 | 766 | 639 | 893 |
| 2019 | 13533 | 11362 | 15704 | 775 | 648 | 901 |
| 2020 | 13710 | 11539 | 15881 | 783 | 657 | 910 |
| 2021 | 13887 | 11716 | 16057 | 792 | 665 | 919 |
| 2022 | 14064 | 11893 | 16234 | 801 | 674 | 928 |
| 2023 | 14240 | 12070 | 16411 | 810 | 683 | 936 |
| 2024 | 14417 | 12247 | 16588 | 818 | 692 | 945 |
| 2025 | 14594 | 12423 | 16765 | 827 | 700 | 954 |
| 2026 | 14771 | 12600 | 16942 | 836 | 709 | 963 |
| 2027 | 14948 | 12777 | 17119 | 844 | 718 | 971 |
| 2028 | 15125 | 12954 | 17296 | 853 | 726 | 980 |
| 2029 | 15302 | 13131 | 17472 | 862 | 735 | 989 |
| 2030 | 15479 | 13308 | 17649 | 870 | 744 | 997 |

*Source: Authors' estimation*

## APPENDIX-B

**Figure B1:** *Production and Yield Forecast of Sugarcane Crop in Pakistan (2013-2030)*

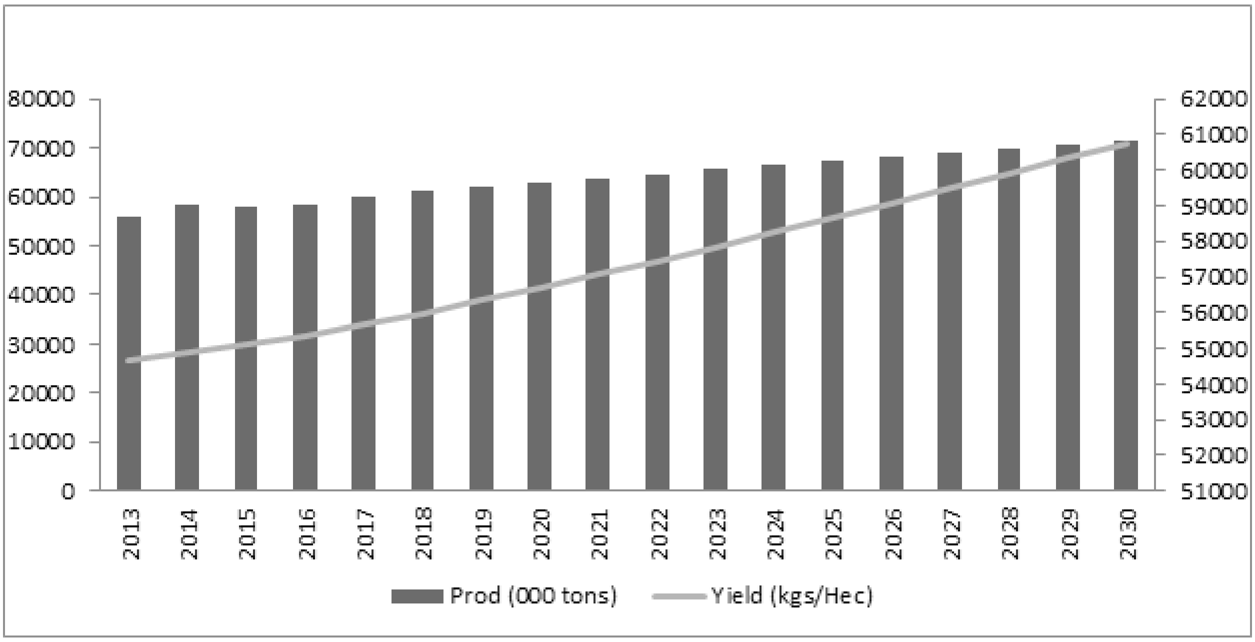



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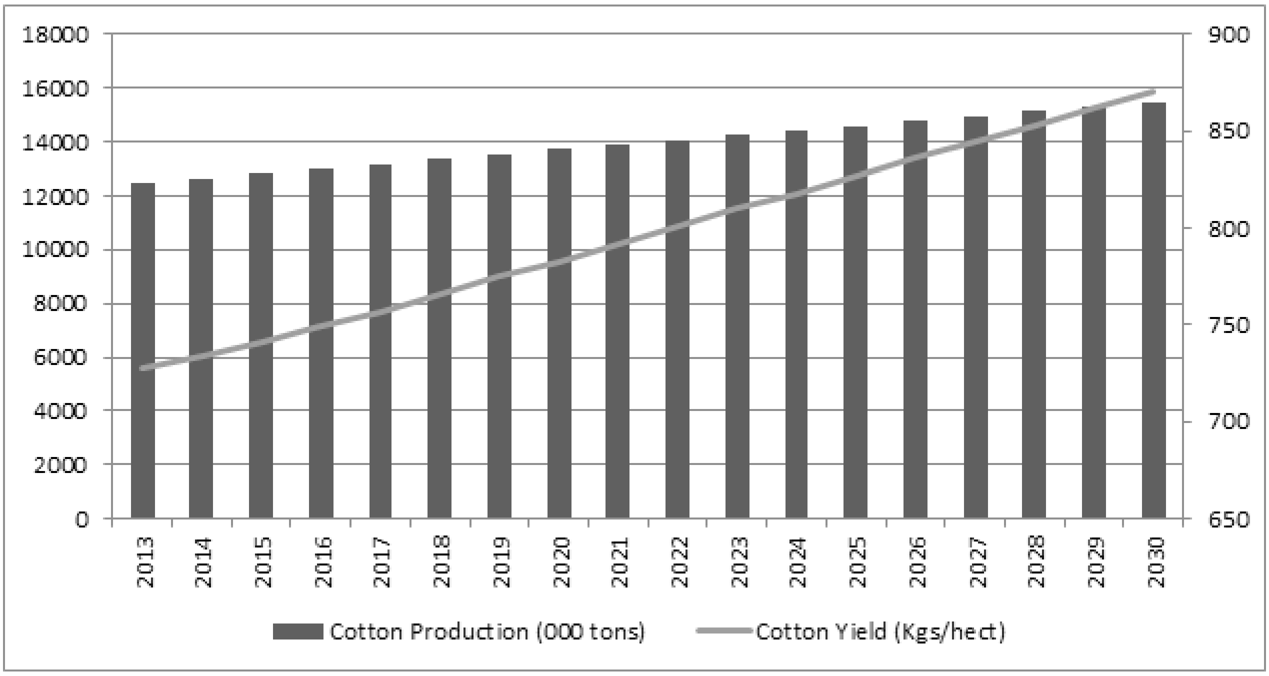
**Figure B2:** *Production and Yield Forecast of Cotton Crop in Pakistan (2013-2030)*




## APPENDIX-C: Correlogram of Residuals

**1.** *d(c_p) c ma(1)*

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | 0.098 | 0.098 | 0.6289 | |
| | | 2 | -0.178 | -0.189 | 2.7496 | 0.097 |
| | | 3 | -0.129 | -0.095 | 3.8917 | 0.143 |
| | | 4 | 0.120 | 0.117 | 4.8970 | 0.179 |
| | | 5 | 0.213 | 0.160 | 8.0971 | 0.088 |
| | | 6 | -0.093 | -0.114 | 8.7170 | 0.121 |
| | | 7 | -0.101 | -0.001 | 9.4671 | 0.149 |
| | | 8 | -0.175 | -0.184 | 11.744 | 0.109 |
| | | 9 | 0.074 | 0.042 | 12.162 | 0.144 |
| | | 10 | 0.038 | -0.051 | 12.272 | 0.198 |
| | | 11 | -0.176 | -0.163 | 14.703 | 0.143 |
| | | 12 | -0.291 | -0.250 | 21.489 | 0.029 |
| | | 13 | 0.136 | 0.225 | 23.014 | 0.028 |
| | | 14 | 0.195 | 0.005 | 26.179 | 0.016 |
| | | 15 | -0.001 | 0.011 | 26.179 | 0.025 |
| | | 16 | -0.107 | 0.009 | 27.186 | 0.027 |
| | | 17 | 0.040 | 0.153 | 27.328 | 0.038 |
| | | 18 | 0.173 | 0.001 | 30.046 | 0.026 |
| | | 19 | 0.106 | 0.071 | 31.088 | 0.028 |
| | | 20 | 0.139 | 0.130 | 32.924 | 0.025 |
| | | 21 | -0.185 | -0.145 | 36.277 | 0.014 |
| | | 22 | -0.055 | -0.043 | 36.580 | 0.019 |
| | | 23 | -0.005 | -0.139 | 36.583 | 0.026 |
| | | 24 | 0.016 | -0.091 | 36.609 | 0.036 |
| | | 25 | 0.035 | 0.184 | 36.737 | 0.046 |
| | | 26 | -0.046 | 0.083 | 36.976 | 0.058 |
| | | 27 | -0.016 | -0.074 | 37.005 | 0.075 |
| | | 28 | 0.015 | 0.188 | 37.032 | 0.094 |

**2.** *c_y c  ma(1) ar(2)  ar(1)*

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.027 | -0.027 | 0.0491 | |
| | | 2 | 0.057 | 0.056 | 0.2616 | |
| | | 3 | 0.026 | 0.029 | 0.3060 | |
| | | 4 | 0.165 | 0.164 | 2.1592 | 0.142 |
| | | 5 | 0.121 | 0.132 | 3.1744 | 0.205 |
| | | 6 | -0.025 | -0.034 | 3.2200 | 0.359 |
| | | 7 | 0.022 | -0.003 | 3.2534 | 0.516 |
| | | 8 | -0.245 | -0.290 | 7.6621 | 0.176 |
| | | 9 | 0.028 | -0.045 | 7.7190 | 0.259 |
| | | 10 | -0.042 | -0.030 | 7.8526 | 0.346 |
| | | 11 | -0.066 | -0.048 | 8.1900 | 0.415 |
| | | 12 | -0.282 | -0.214 | 14.490 | 0.106 |
| | | 13 | 0.063 | 0.134 | 14.813 | 0.139 |
| | | 14 | 0.089 | 0.153 | 15.462 | 0.162 |
| | | 15 | -0.021 | 0.057 | 15.500 | 0.215 |
| | | 16 | -0.146 | -0.156 | 17.329 | 0.185 |
| | | 17 | 0.033 | 0.048 | 17.423 | 0.234 |
| | | 18 | 0.111 | 0.060 | 18.532 | 0.236 |
| | | 19 | 0.033 | -0.008 | 18.636 | 0.288 |
| | | 20 | 0.139 | 0.037 | 20.449 | 0.252 |
| | | 21 | -0.157 | -0.128 | 22.848 | 0.197 |
| | | 22 | -0.013 | -0.054 | 22.866 | 0.243 |
| | | 23 | -0.066 | -0.133 | 23.315 | 0.274 |
| | | 24 | -0.098 | -0.316 | 24.310 | 0.278 |
| | | 25 | 0.011 | 0.109 | 24.324 | 0.330 |
| | | 26 | -0.075 | 0.151 | 24.943 | 0.353 |
| | | 27 | -0.043 | -0.003 | 25.153 | 0.397 |
| | | 28 | 0.005 | 0.103 | 25.156 | 0.454 |

**3.** *s_p c ar(1) ma(4) ma(2)*

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.168 | -0.168 | 1.8697 | |
| | | 2 | -0.138 | -0.171 | 3.1391 | |
| | | 3 | -0.030 | -0.091 | 3.2016 | |
| | | 4 | 0.030 | -0.019 | 3.2630 | 0.071 |
| | | 5 | 0.093 | 0.083 | 3.8799 | 0.144 |
| | | 6 | -0.205 | -0.181 | 6.8854 | 0.076 |
| | | 7 | -0.030 | -0.084 | 6.9498 | 0.139 |
| | | 8 | -0.085 | -0.178 | 7.4893 | 0.187 |
| | | 9 | 0.016 | -0.089 | 7.5098 | 0.276 |
| | | 10 | 0.052 | -0.020 | 7.7166 | 0.358 |
| | | 11 | -0.183 | -0.201 | 10.353 | 0.241 |
| | | 12 | 0.080 | -0.041 | 10.867 | 0.285 |
| | | 13 | 0.077 | 0.007 | 11.350 | 0.331 |
| | | 14 | 0.106 | 0.067 | 12.287 | 0.342 |
| | | 15 | 0.004 | 0.038 | 12.289 | 0.423 |
| | | 16 | 0.081 | 0.164 | 12.855 | 0.459 |
| | | 17 | -0.004 | 0.002 | 12.856 | 0.538 |
| | | 18 | 0.021 | 0.080 | 12.895 | 0.610 |
| | | 19 | 0.044 | 0.083 | 13.075 | 0.667 |
| | | 20 | -0.066 | 0.039 | 13.487 | 0.703 |
| | | 21 | -0.052 | 0.022 | 13.755 | 0.745 |
| | | 22 | -0.019 | 0.036 | 13.793 | 0.796 |
| | | 23 | -0.087 | -0.076 | 14.576 | 0.800 |
| | | 24 | -0.041 | -0.037 | 14.752 | 0.835 |
| | | 25 | -0.025 | -0.030 | 14.817 | 0.870 |
| | | 26 | 0.005 | -0.059 | 14.820 | 0.901 |
| | | 27 | -0.018 | -0.048 | 14.857 | 0.925 |
| | | 28 | 0.039 | -0.048 | 15.038 | 0.940 |

**4.** *s_y c ar(1) ma(1)*

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | 0.110 | 0.110 | 0.8047 | |
| | | 2 | -0.215 | -0.230 | 3.9151 | |
| | | 3 | 0.007 | 0.066 | 3.9181 | 0.048 |
| | | 4 | 0.209 | 0.161 | 6.9620 | 0.031 |
| | | 5 | -0.096 | -0.147 | 7.6135 | 0.055 |
| | | 6 | -0.125 | -0.015 | 8.7346 | 0.068 |
| | | 7 | -0.016 | -0.053 | 8.7524 | 0.119 |
| | | 8 | 0.072 | 0.022 | 9.1382 | 0.166 |
| | | 9 | -0.097 | -0.084 | 9.8520 | 0.197 |
| | | 10 | -0.254 | -0.227 | 14.855 | 0.062 |
| | | 11 | -0.057 | -0.031 | 15.110 | 0.088 |
| | | 12 | 0.006 | -0.113 | 15.113 | 0.128 |
| | | 13 | -0.084 | -0.069 | 15.694 | 0.153 |
| | | 14 | -0.046 | 0.021 | 15.867 | 0.197 |
| | | 15 | 0.087 | 0.010 | 16.516 | 0.222 |
| | | 16 | 0.073 | 0.036 | 16.974 | 0.258 |
| | | 17 | -0.098 | -0.115 | 17.822 | 0.272 |
| | | 18 | 0.027 | 0.065 | 17.887 | 0.331 |
| | | 19 | 0.083 | -0.033 | 18.533 | 0.356 |
| | | 20 | 0.074 | 0.014 | 19.060 | 0.388 |
| | | 21 | -0.057 | -0.042 | 19.380 | 0.433 |
| | | 22 | -0.016 | -0.072 | 19.406 | 0.496 |
| | | 23 | -0.060 | -0.132 | 19.775 | 0.536 |
| | | 24 | 0.079 | 0.078 | 20.425 | 0.556 |
| | | 25 | 0.023 | 0.023 | 20.484 | 0.613 |
| | | 26 | 0.067 | 0.123 | 20.977 | 0.640 |
| | | 27 | -0.023 | -0.050 | 21.037 | 0.691 |
| | | 28 | 0.070 | 0.108 | 21.609 | 0.710 |