Estimating the Effect of Biennial Olive Bearing to Forecast Syrian Olive- Oil Production by Using Box-Jenkins (ARIMA) Methodology

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Abstract

This study aimed to analyze the time series of olive-oil production in Syria and thus estimate the effects of biennial/alternate fruit-bearing phenomena and determine the appropriate forecasting model based on The Box-Jenkins method. It used annual data of olive-oil production over 58 years from 1961 to 2018. The results showed that the time series of olive-oil in Syria is non-stationary, and it is characterized by three trends: the first is a general trend that tends to rise; the second is a cyclical trend, i.e., biennial bearing (BB)that leads to the exchange of production every other year; and the third is a random trend resulting from abnormal climate changes or security disorders and their economic effects. The biennial bearing phenomenon is characterized by instability and irregularity, which made forecasting more difficult.

It has been found that BB was responsible for 21.7% of the rise in production over the years of positive/bearing/production (increase above the general production of the series). In contrast, this factor was responsible for 18.9% of the decline in production over the years of negative/non-bearing production.

The best model for forecasting live-oil production was ARIMA (3.1.1), but the lag parameter Y_{t-2} was non-significant. The self-regression parameters (AR) reveal that the behavior of this time series has often been determined by its values in the first and third recent years, while the moving average parameters (MA) indicate that the behavior of the time series (Y_t)is often determined in terms of current random noise and previous random noise.

Keywords: *Olive production in Syria, Box-Jenkins models, time series, biennial/alternate bearing, cyclical trends, ARIMA*

I. INTRODUCTION

Olive production in Syria has been developed largely since the beginning of the current century, ranking the fourth or fifth at the world level. At the national level, olive production is the main key to the Syrian economy, due to its high contribution to national income (3.5-1.5%) and to agricultural income (9-5% as per bearing year) [1]. In addition, it employs a notable share of the workforce, where the number of households working in olive cultivation and processing was about 377 thousand, i.e., 15% of the total workforce [2]. Olive production is an income and livelihood source for more than 20% of Syria's population [2].

Olive production in Syria is highly affected by the phenomenon of biennial/alternate bearing (BB), which usually affects many types of fruit trees, referring to the systematic alternation of fruit production. This appears through the sequences of a good production year (bearing year) followed by a low or zero production one (non-bearing year), without being a result of harsh or irregular climatic factors. BB is mainly related to genetic and physiological reasons; it is very complicated as a result of the interaction of many overlapped factors such as fertilization, the omission of pruning, climate elements, cultivar type, and tree sanitation [3]. BB may take different time dimensions: First, it may be stable when the bearing is at the same trend, a year of heavy bearing followed by low bearing one. Second, it may be unstable with heavy bearing in one year and low bearing in the two or three next years. Third, this alternation may be irregular when the bearing is unstable for many sequenced years; it may have an increase for three or more years, followed by a decrease in the next years [2].

The Syrian agricultural policy has focused on disseminating new agricultural techniques to face the BB phenomenon, such as systematic pruning, fertilization, and resistant cultivars; nevertheless, its effect is still high and often drops oil production to half nearly at years of low (non-bearing) production [4]. In general, olive-oil production has been duplicated in Syria during the recent decade, which is mainly related to the increasing area, especially in the inland regions, which are less affected by BB rather than the coastal region [5].

The impact of the BB phenomenon during the recent period has led to high variance in olive-oil time series, complicating the prediction process in the short run. Especially when the trend of this phenomenon became irregular, at which the effect differed from one year to another. On the other hand, this variance does not depend only on the gap between bearing years and non-bearing ones, but also on variation within bearing years in addition to variation within non-bearing years too. Therefore, the percentage of decrease often differs within non-bearing years, and the same for the percentage of increase in the bearing years.

Consequently, the temporal development of olive-oil production in Syria has a fluctuant and unstable trend, resulting in the complexity of constructing suitable forecasting models, especially by using conventional statistical methods as for other agricultural goods. This requires focusing on alternative, unconventional models that consider both sides, cyclical changes of production, and autocorrelation within different years. This actually justifies the application of Auto-Regressive Integrated Moving Average(ARIMA) as an eligible method to predict olive- oil production in Syria, given that the more prediction efficiency, the better planning efficiency towards production and marketing.

This research was conducted to:

1. analyze the main elements and components of the olive-oil time series in Syria.
2. Estimate the effect of biennial/alternate bearing on annual changes of olive oil.
3. Build on a suitable prediction model using Box-Jenkins Method.

II. MATERIALS AND METHODS

This study is based on econometric prediction models, Box-Jenkins models, which were tested on time series by Gwilyn Jenkins and George Box in 1970. This method extracts the predictable changes of observed data by partitioning this time series into many components. These include stationery, autoregressive, and moving average components. These components work for purifying time series to obtain predictable data free of econometric errors and contains random noise only.

III. RESULTS AND DISCUSSION

A. *Time series data of olive-oil production*

The targeted time series is the annual data of producing olive oil in Syria, which lasted over 58 years, from 1961 to 2018 (Table 1).

Table1. Time series data for olive-oil production

Year	Production (ton)	Growth %	Year	Production (ton)	Growth %	Year	Production (ton)	Growth %
1961	18000		1981	44520	-46.6	2001	95384	-42.3
1962	20447	13.6	1982	94838	113.0	2002	194599	104.0
1963	15093	-26.2	1983	27264	-71.3	2003	103947	-46.6
1964	25512	69.0	1984	51000	87.1	2004	201964	94.3
1965	13598	-46.7	1985	35000	-31.4	2005	123143	-39.0
1966	24620	81.1	1986	72000	105.7	2006	252353	104.9
1967	24155	-1.9	1987	32000	-55.6	2007	98294	-61.0
1968	22444	-7.1	1988	86000	168.8	2008	156338	59.1
1969	25648	14.3	1989	21000	-75.6	2009	168163	7.6
1970	15495	-39.6	1990	86000	309.5	2010	194995	16.0
1971	22247	43.6	1991	39000	-54.7	2011	208329	6.8
1972	33394	50.1	1992	103000	164.1	2012	193829	-7.0
1973	13715	-58.9	1993	60139	-41.6	2013	159595	-17.7
1974	44412	223.8	1994	99895	66.1	2014	66676.38	-45.9
1975	33244	-25.1	1995	84852	-15.1	2015	155260.83	132.9
1976	55898	68.1	1996	126613	49.2	2016	113634.97	-26.8
1977	38056	-31.9	1997	76924	-39.2	2017	187000	27.2
1978	69573	82.8	1998	144820	88.3	2018	115360	-20.2
1979	40428	-41.9	1999	80104	-44.7	-	-	-42.3
1980	83385	106.3	2000	165354	106.4	-	-	104.0

Source: FAOSTAT, [6] & Syrian Agricultural Statistical Abstract [7].

According to the annual growth rate, two types of years can be recognized: years of positive production (bearing years), which have a positive growth rate versus years of negative growth rate (non-bearing years). Moreover, the time series was also equally divided between these two types of years (29 years each type).

B. Stationary tests of time series.

The problem of mean instability has resulted from autocorrelation [8]. In regression models, the problem of autocorrelation indicates a correlation among successive values of random error. In time series, autocorrelation refers to the correlation between successive values of random error across successive periods.

If the series is inconstant invariance (variance instability), a proper transformation of data is used by natural logarithm. If the series is inconstant for the mean, the trend term/difference factor is used (d) [9].

This is done by taking the first difference of data (d = 1) according to Dicky and Fuller (df) test [10], which assumes a randomized sequence following the type of auto-regression in the first order, i.e., the difference ΔYt depends on the value of previous year:

$\Delta Y_t = Y_t - Y_{t-i} = f\,(Y_{t-i}) + u_t$

ΔYt: First difference

i: Number of lags(order of the year whose value affects the value of current year).

$U_t = e_t$: White noise context (random noise of white noise type)

If the series does not settle after the first difference, the second difference is taken (d = 2) according to the Expanded Augmented Dicky and Fuller (ADF) test [11].

Accordingly, the stability of the time series will be examined using the sequence plot or the scattering curve, i.e., the graph of actual data studied over time. It is useful to identify the characteristics of the time series in terms of trend or variance instability, the existence of missing values or outliers within the series, or other practical problems, i.e., to identify the causes of instability, if any. So that the series is generally stable, this curve should be centered on a fixed average.

The historical data of the study ranged from 1961 to 2018, was represented by linear form, as shown in Figure (1). The horizontal axis represents a specific year, while the vertical one represents the value associated with production in tons.

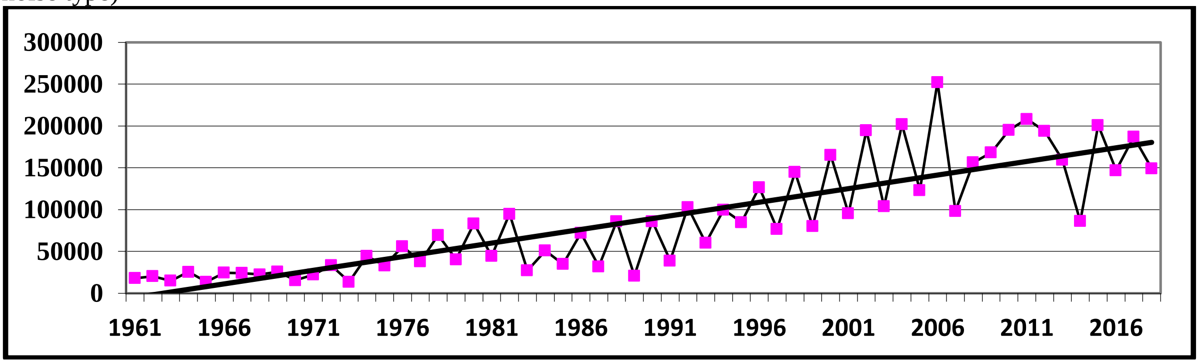

Figure 1. Sequence plot or scatter curve of original data for olive-oil production in Syria during (1961-2018)

This graph shows that the time series based on observed data for olive-oil production is not static invariance. It is characterized by the existence of a multiple cyclical trends and an increasing general trend. Therefore, it belongs to DS type, i.e.., Difference Stationery. It also includes unstable random trend, particularly during (2012-2016), that is during the Syrian crisis, which negatively affected olive-oil production, so it became more irregular than other previous years.

Accordingly, this series is non-stationary. To test this apparent result statistically, autocorrelation coefficients were estimated for the time series of olive-oil production in Syria during (1960-2011), as shown in Figure (2).

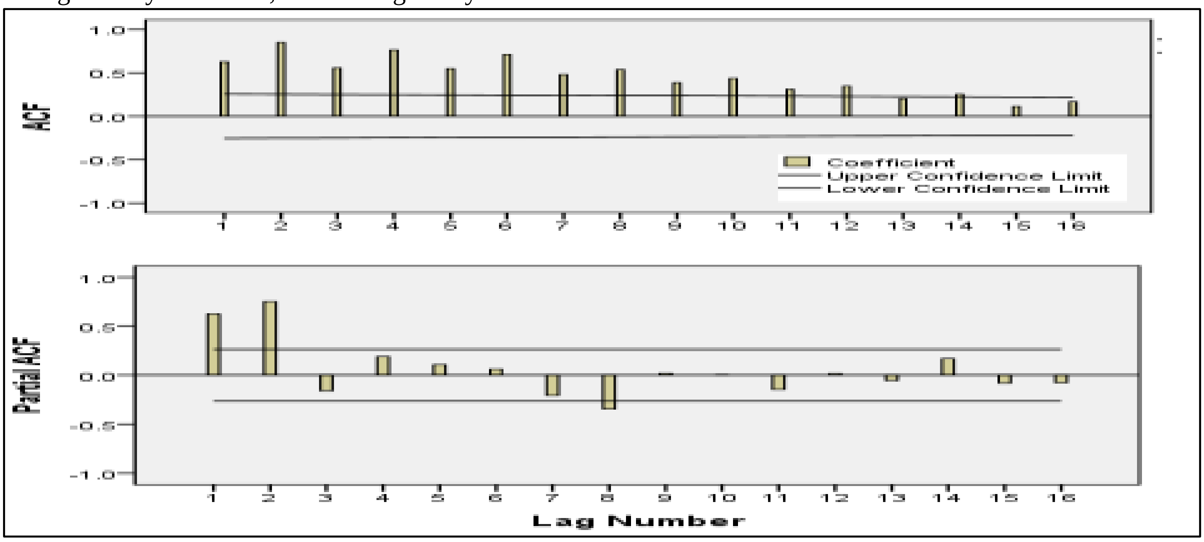

Figure 2.Auto-correlation and partial auto-correlation curves (Corrologram) of original data.

If the time series is stationary (stable), all ACF and PACF values of the sample must be within the confidence intervals except for first or second lags, which can be outside confidence limits. This means that the value of auto- or partial correlation coefficient at the lag (k) should be within the range [-0.25, +0.25], at significance level (95%) [12].

For the original time series of olive-oil production in Syria, however, most of the ACF values were found to be outside confidence levels, while all PACF values were within those levels except for first and second lags.

In general, the recent Figure shows that many spikes were found in ACF and PACF curves of the original model, indicating series instability.

The Ljung and Box test was used to test the overall parameters of autocorrelation function using Q.Stat. All autocorrelation coefficients were greater than the value of χ^2 at significance level (5%) based on the degree of freedom (number of lags). This indicates this series is unstable on average, so the null hypothesis is rejected, which indicates that the coefficients of autocorrelation are equal to zero and accept the alternative hypothesis.

C. It is stabilizing the time series of olive-oil production in Syria during 1961-2018.

It is clear from the previous tests of autocorrelation and partial autocorrelation that this series is unstable on average. As evidenced by the form of the time series of the original data that this series is not static invariance, characterized by the existence of a general trend and a cyclical trend (rise and fall), which means that the series is apparently unstable. Accordingly, this problem will be addressed by Smoothing out the real-time series.

This is often done by deriving the components of the time series, cyclical variations, seasonality, and irregularity as the classical model of the time series consists of four elements expressed as:

$$Y_t = C_t \cdot S_t \cdot I_t \cdot T_t$$

T(trend), C (Cyclical Variations)S (Seasonal Variations), I (Irregular Variations, Y: The value of the dependent variable at a certain time [13].

The penultimate step is to isolate the cyclic component and eliminate the irregularity from the data by calculating the average values of the recent total index (the cyclical and irregular components) in each cycle along with the series [14].

In our data, there are two cyclical indexes, one for bearing years and other for non-bearing, so in the final stage of this step, the series data should be smoothed out by eliminating the cyclical component. For that, the original values of bearing and non-bearing years are multiplied by its cyclical indexes consecutively. Finally, the resulted time series supposed to be characterized by a general trend only. However, this first smoothing of cyclical variations was not enough to eliminate the cyclical effect completely, especially in the last ten years of the series. But this series appears to be less stable around the average, i.e., with unfixed variance. That can be explained by increasing the influence of chaos or abnormality component in the recent period, as well as the wide impact of BB, where each year's production is affected by the production of the first and second years preceding it. Supposing a non-bearing year, its production will often be influenced by the production of the previous bearing year and production of the previous-bearing year, and vice versa for the bearing years. This matter can be addressed by applying the moving averages method to the adjusted data again, thus obtaining a new series that appears to have a stable average, as shown in Figure (3).

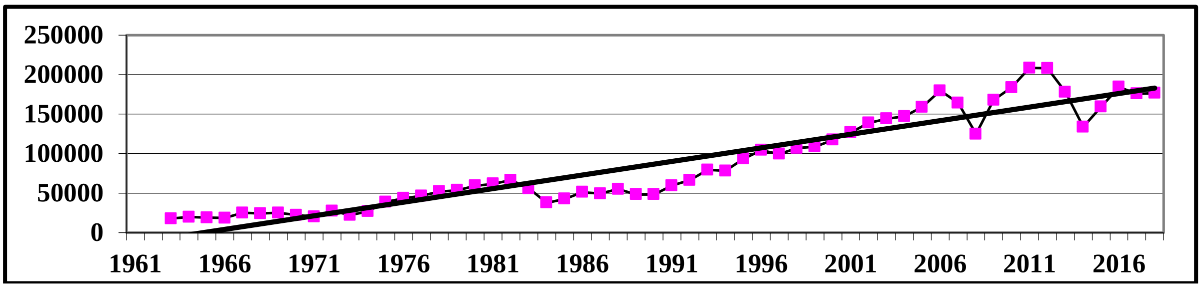

Figure 3. Adjusted time series in the first step following second smoothing by moving averages

It is clear from the previous Figure that the variance is not relatively stable over time, i.e., this adjusted series is still characterized by the existence of the Trend problem. That is, it has become the TS type (Trend stationery), where a general trend increasing over time was noticed. Therefore, this series is still needed to be stabilized. This problem is solved in two stages:

- First: Log-Transformation of the modified series for variance stabilization.
- Second: Using the first-order difference parameter ($\Delta y = y_t - y_{t-1}$) to stabilize the average, i.e., to move out the general trend.

Finally, a new series was obtained, as shown in Figure (4).

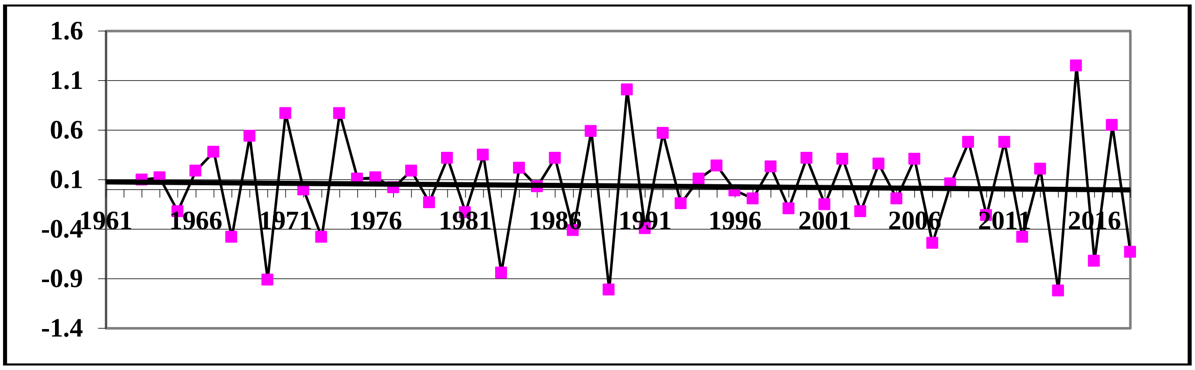

Figure 4. The time series in the second step after removing the vector and achieving the conditions of stationary.

This Figure shows that the adjusted series became more stationary. The new pattern for this series shows that the variance tends to be stable, and there is no general trend over time. This indicates the stability of the adjusted series after the first and second smoothing, and thus can say that this series has become stable (i.e., in expectation), and is ready to apply the Bok-Jenkins methodology for data analysis.

D. Determination of model rank:

Defining the random context that generates the time series is critical for selecting the suitable prediction model. This can be decided depending on auto-correlation and partial correlation coefficients. Re.[12] suggested that the appropriate model rank should be determined by using ACF and PACF form, as shown in Figure 5.

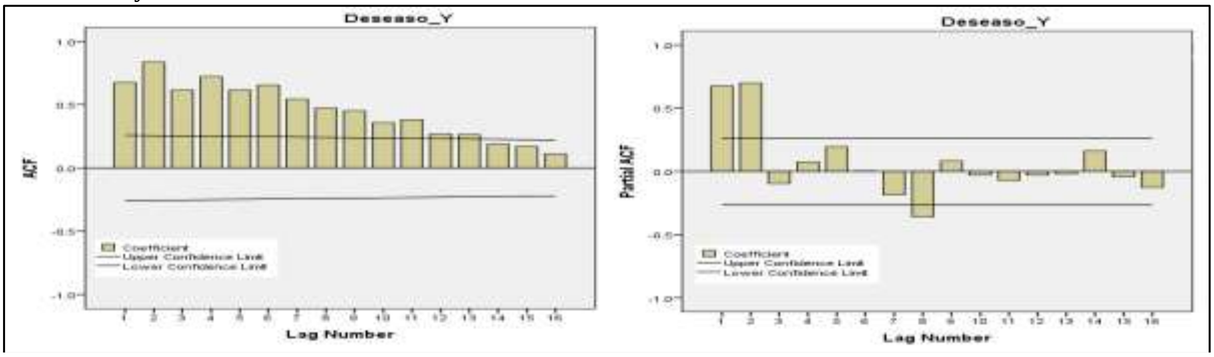

Figure 5. Autocorrelation and partial autocorrelation curves of adjusted data (Deaseso_y)

The curve of ACF function decreases gradually with increasing lag periods (K), and it gradually declines and follows the behavior of the sinusoidal function, leading to the proposed model AR(p). This behavior appears to be less notable in the PACF, leading to the suggestion of MA(0) or MA(q).

Given that the number of non-significant coefficients of partial correlation is three, as shown in the recent correlogram figure, then AR (3) can be suggested.Since the original function is stabilized with one difference and with a logarithmic transformation, the proposed model is the corresponding ARIMA (3, 1, 1) With formula / ARIMA AR = [3,1,1] DIFF = 1 MA = 1.

However, when using the Expert Modelermethod, another proposed model is ARIMA (1, 1, 0), meaning that both ARIMA (3, 1, 1) and ARIMA (1, 1, 0) can be a candidate. Consequently, the two models have been applied to the adjusted series (Deseaso_y) and compared based on a set of tests accompanying each model, as shown in Table (2).

Table 2. Model Fit Statistics

Measures	ARIMA(1,1,0)	ARIMA(3,1,1)
RMSE	28188.2	26088.4
MAPE	24.7	26.3
MaxAPE	132.3	132.6
MAE	19012.4	17030.4
MaxAE	93833.7	92065.3
Normalized BIC	20.6	20.6

The best model is that achieves the minimum values for each of the following criteria [15].

1. Root Mean Square Error {RMSE}
2. Mean Absolute Percentage Error {MAPE}
3. Mean Absolute Error {MAE}
4. Max value for Absolute Percent Error
5. (MaxAPE) and Max value for Absolute Error (MaxAE), which are often unnecessary.

Thus, the general form of the model's estimated equation is:

$$Y_t = \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \emptyset_3 Y_{t-3} + u_t - \theta_1 u_{t-1}$$

- u_t: The random error of white noise type, which has a normal distribution and a constant variation [24].

The assumption behind the autoregression model of the third rank is that the behavior of the time series $Y_t$is often determined by its values for the previous three years. That is, what will happen in the period t depends on what happens in the period t-1, as well as what will happen in the period t-2 and t-3... While the assumption behind the moving average model is that the behavior of the time series $Y_t$is often determined in terms of current random error and previous random error.

E. estimation of ARIMA Model Parameters (3,1,1)

Once the general model for the olive-oil series has determined, the parameters of the ARIMA model will be estimated using the SPSS program based on the maximum likelihood function [8]. The results could be expressed as in Table (3).

As a result, ARIMA (3, 1, 1) has achieved the lowest values of most of the previous criteria,
therefore it is better than ARIMA (1, 1, 0) to for cast the time series of olive-oil production.

Accordingly, the general form of the model equation can be written, taking into account the negative sign of the parameters of θ, and the positive signal of the parameters of ϕ, since most computer programs do not observe this rule [16].

- $|\emptyset| < 1$: the parameter of the self-regression model, which is smaller than one absolute value to achieve the stationary condition.
- $|\theta| < 1$: The parameter of the moving averages model, which is smaller than one absolute value to achieve the stationary condition.

Strikingly, the coefficient of the lag (Y_{t-2}) has been nullified; i.e., the production of each individual year in the series is not significantly affected by the production of the second previous year but is significantly affected by the value of the first and third previous years.

Table 3. Estimates of the ARIMA model for modified olive oil time series (Deseaso_y) (the original series after disposal).

		Estimate	SE	t	sig
No Transformation	**Constant**	2947.492	1021.346	2.886	0.006
AR	**Lag 1**	-0.501	0.130	-3.847	0.000
	Lag 3	-0.369	0.124	-2.975	0.004
Difference		1			
MA	**Lag 1**	0.470	0.144	3.259	0.002

It has been noted that the estimated coefficients are significant, which is not equal to zero, so the the null hypothesis is rejected.$|\theta, \emptyset| < 1$,i.e., is greater than one in absolute terms, satisfies the stationary and reflective condition of the auto-regression parameters.

The problem of autocorrelation was examined again using the Ljung-Box test, where the sample statistics also indicate the independence of the sample values, as shown in Table (4)

Table 4. Model statistics for ARIAM (3,1,1).

Model	Number of predictors	Model Fit statistics	Ljung-Box Q(18)		
		Stationary R-squared	Statistics	DF	Sig.
Deaseso_y (ton)	0	0.746	9.168	15	0.869

The high Ljung-Box Q statistic indicates acceptance of the hypothesis that there is no autocorrelation between sample values.

$$H_o : \rho_1 = \rho_2 = ... = \rho_K = 0$$

[17].

This hypothesis is significant. This means that the sample values are independent, and the correlation between them equals zero, leading to stable time-series predictions.

Consequently, the corresponding prediction equation for the ARIMA model (3.1.1) can be written as follows [18]:

$(1-B)(1+0.501B)(1+0.369B)Y_t=2947.492 \quad +_{ut} \quad - 0.47_{ut-1}$

B: Backshift Operator

$\nabla^d Y_t= (1-B)^d Y_t$

Thus, according to this equation, the production of the current bearing year depends on the production of the previous two bearing years and is also affected by a random error of the previous year.

F. Testing the model fit:

If the model is appropriate, the model errors will have random variations with a zero mean and a constant variation. In another expression, these types of errors are called white noise series.

The analysis of model errors depends on the estimates of these errors, which depends on the model's residuals. The residuals or the predictions errors are the actual values subtracted from the estimated ones,

To determine the independence and randomness of residues and make the final decision about the model fit, the confidence level test must be used, assuming that the values of auto-correlations coefficients are within the confidence range with 95% probability, under the following formula:

$$\left\{-1.96\left[\frac{1}{\sqrt{n}}\right] \leq p_k(a_t) \leq +1.96\left[\frac{1}{\sqrt{n}}\right]\right\} = 0.95p_r$$

once the above formula is achieved, it proves that the residues are distributed randomly and that the used model represents the data adequately and can be used for prediction. Thus, the autocorrelations of the residues are normally distributed at zero means and 1 / n variation [19].

This also clear in the correlogram Figure for autocorrelation and partial autocorrelation function (Fig. 6), where there is no autocorrelation (ACF or PACF) between the model residuals within confidence limits (25%). Therefore, the residues follow the white noise type, i.e., the residues are independent and distributed normally at a zero mean and a variation of σ2.

In addition, one of the normal distribution tests can also be used for residues such as the one-sample Kolmogorov-Smirnov Test. The statistical value of this test is (0.112) at the significance level (sig = 0.077), meaning that it is non-significant at 1% or 5%.

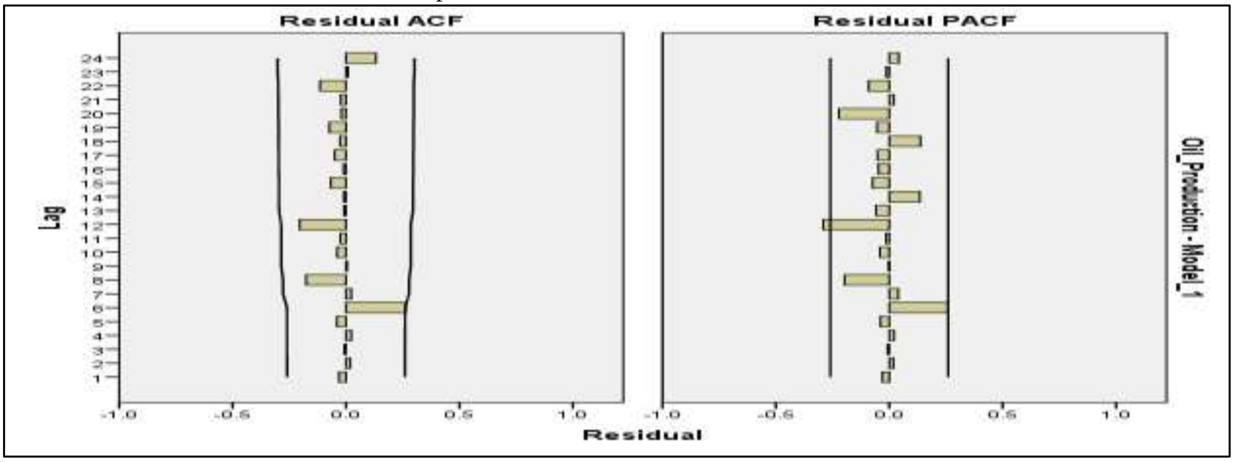

Figure 6. Autocorrelation curves and partial autocorrelation for the errors of a model (3, 1, 1) based on adjusted data (Deaseso_y).

Therefore, the null hypothesis is rejected and that the residues do not follow the normal distribution. Otherwise, this normal distribution is also clear when drawing the histogram for the residues, as in Figure 7.

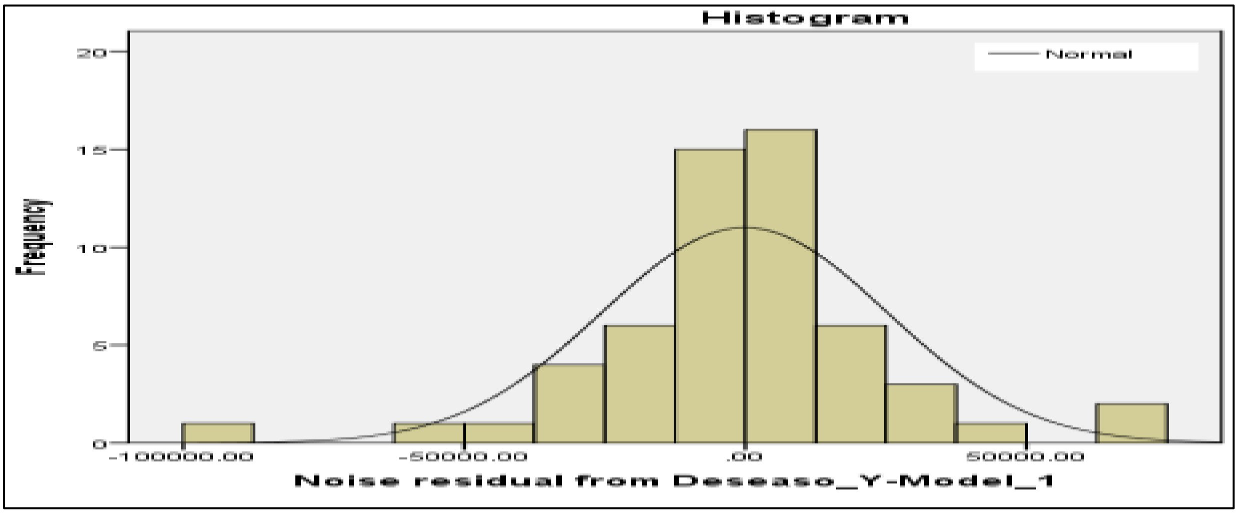

Figure (7). The histogram curve for the residues of ARIMA model (3.1.1) based onadjusted data (Deaseso_y)

It is clear that the model residues are distributed normally except for four values, which are the values of the years 2008, 2009, 2011, 2014, where olive production in these years was characterized by random shocks. Many random variables influenced the general trend of time series and forced it to deviating from the general line. The main responsible factor is instability (irregularity) ofBB during that period. Building on the normal trend of BB phenomenon, it is assumed that 2008 will be a bearing year but its production has decreased significantly compared to 2007 and 2009, while it gradually tendsto increase under the absence of BBover the four following years (2009-2012). Suddenly, this production has got back again to decrease in 2013. This decline continued in 2014, which is supposed to represent a bearing year, anda further decline in production compared to 2013. After the end of this volatility period, BB started to stabilize again in the subsequent years.

In general, these changes are due to unpredictable factors, such as abnormal climatechanges. The drought that hit Syria in 2007 affected olive-oil production in 2008 and several years later. In addition to the serious security events in Syria, resulting in disturbance of time series during 2008-2014 compared to the rest periods.This disorder cannot be expressed mathematically within the overall context of the whole series, leading to anomalies of corresponding values for the four years mentioned. Despite these abnormal values, the ARIMA model (3.1.1) is still in accordance with statistical standards, and is considered as the most accurate and reliable model for forecasting olive-oil production in Syria, especially when excluding previous anomalies**.**

G. Use of ARIMA (3.1.1) for forecasting olive-oil production for subsequent years:

Prediction is one of the main objectives of any study of time series analysis. Due to recent results ARIMA model (3.1.1) was used to predict olive-oil production in Syria during (2019-2025), as shown in Table 5.

Table 5. Predicted values for olive-oil production over seven years (2019- 2025).

Year	Olive oil (ton)
2019	228740.1
2020	140747.5
2021	230057.1
2022	151762.3
2023	228913.6
2024	162868.7
2025	230311.9

It appears from the prediction series that production will rise in 2019 as a bearing year, while in 2020 it will decrease as a non-bearing year, and thus corresponding to the same pattern for the rest of the years. However, the overall trend keeps on high increasing rates for both bearing years and non-bearing ones. The ratefor any year depends on production amount of the first and third previous years, as well as the amount of random error for the first previous year, based on the components of previous forecast formula.

Therefore, it is possible to say that this model accurately reflects the time series for olive-oil production in Syria at confidence levels of 1% and 5%.The selected model has been statistically appropriate for the observed data, as shown in Figure (9). Noting that the observed values used to construct the predictive values of this model are the values that have been adjusted by smoothing process, leading to building an adjusted variable of olive-oil production (Deseao_y), as discussed earlier.

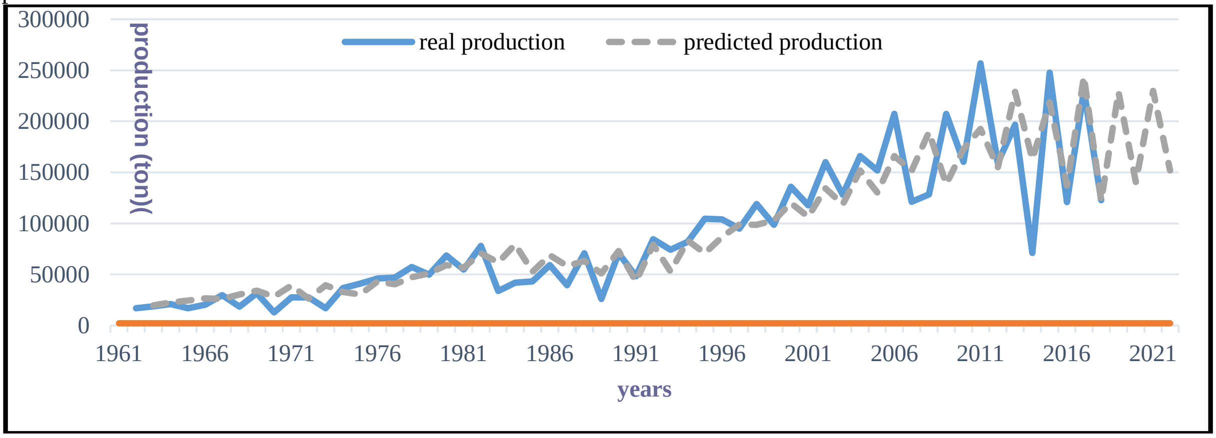

Figure 9. Observed and predicted values of olive oil using ARIMA model (3, 1, 1)

It is noted that the predictive curve takes an increasing generaltrend and a cyclical trend that often corresponds to the real curve, except in periods of anomalies resulting from chaos or random changes. Thiscannot be achieved using traditional forecastingmodels.

IV. CONCLUSIONS

1) Olive-oil production in Syria is characterized by three trends of development:
   - The first is a general trend that risesover time.
   - The second is a cyclical trend, i.e. alternate bearingevery other year (BB phenomenon), as the bearing year (high production) is often followed by a non-bearing year (low or zero production).
   - The third is a random trend resulting from abnormal climate changes or from security disorders and their economic effects.
2) Biennial bearingin olive production is characterized by instability, although it takes a binary pattern in most of the periods, but for some other times it takes a triangular pattern (one bearing year versus two non-bearingyears or vice versa). On the other hand, there is no clear trend for olive production which can be absent or decreased in some periods, especially during 2008-2011, which can be attributed to erratic climate changes.
3) The cyclical trend into the olive production series is attributed to BB phenomenon, which is responsible for 21.7% of total increased production in bearingyears (increase above level of general production of the series or so-called base line).In contrast, this factor is responsible for 18.9% of declined production in non-bearing years.
4) The traditional predictive models, such as the exponential model chosen in the first part are predictive-poor models compared to ARIMA model (3, 1, 1). Traditional models focus on the general trend while omitting the effects of cyclical changes.
5) The time series for olive-oil production in Syria becomes more stable when reducing the cyclical effects, which shows the importance of adopting modern techniques that reduce the impact of BB phenomenon on olive production.

According to all above, we suggest the following:

1. Focus on ARIMA (3, 1, 1) model to forecast olive production in Syria assuming no abnormal changes.
2. Taking the cyclical effects on production into account when planning olive-oil production.

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