

TIME SERIES ANALYSIS

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1. Introduction

A Time Series (TS) is a sequence of observations ordered in time. Mostly these observations are collected at equally spaced, discrete time intervals. When there is only one variable upon which observations are made then we call them a single time series or more specifically a univariate time series. A basic assumption in any time series analysis/modeling is that some aspects of the past pattern will continue to remain in the future. Also under this set up, often the time series process is assumed to be based on past values of the main variable but not on explanatory variables which may affect the variable/ system. So the system acts as a black box and we may only be able to know about 'what' will happen rather than 'why' it happens. So if time series models are put to use, say, for instance, for forecasting purposes, then they are especially applicable in the 'short term'. Here it is tacitly assumed that information about the past is available in the form of numerical data. Ideally, at least 50 observations are necessary for performing TS analysis/ modeling, as propounded by Box and Jenkins who were pioneers in TS modeling.

As far as utility of time series modeling in agriculture is concerned, its application in the area of statistical forecast modeling needs hardly any emphasis. Lack of timely forecasts of, say, agricultural production, especially short-term forecasts has often proved to be a major handicap to planners. Various statistical approaches viz. regression, time series and stochastic approaches are in vogue for arriving at crop forecasts. Every approach has its own advantages and limitations. Time series models have advantages in certain situations. They can be used more easily for forecasting purposes because historical sequences of observations upon study variables are readily available from published secondary sources. These successive observations are statistically dependent and time series modeling is concerned with techniques for the analysis of such dependencies. Thus in time series modeling, the prediction of values for the future periods is based on the pattern of past values of the variable under study, but not generally on explanatory variables which may affect the system. There are two main reasons for resorting to such time series models. First, the system may not be understood, and even if it is understood it may be extremely difficult to measure the cause and effect relationship, second, the main concern may be only to predict what will happen and not to know why it happens. Many a time, collection of information on causal factors (explanatory variables) affecting the study variable(s) may be cumbersome /impossible and hence availability of long series data on explanatory variables is a problem. In such situations, the time series models are a boon for forecasters.

Decomposition models are among the oldest approaches to time series analysis albeit a number of theoretical weaknesses from a statistical point of view. These were followed by the crudest form of forecasting methods called the moving averages method. As an improvement over this method which had equal weights, exponential smoothing methods came into being which gave more weights to recent data. Exponential smoothing methods have been proposed initially as just recursive methods without any distributional assumptions

about the error structure in them, and later, they were found to be particular cases of the statistically sound AutoRegressive Integrated Moving Average (ARIMA) models.

In early 1970's, Box and Jenkins pioneered in evolving methodologies for time series modeling in the univariate case often referred to as Univariate Box-Jenkins (UBJ) ARIMA modeling. In course of time, various organisations/ workers in India and abroad have done modeling/ forecasting (of course, not necessarily for agricultural systems) based on time series data using the different methodologies viz. time series decomposition models, exponential smoothing models, ARIMA models and their variations such as seasonal ARIMA models, vector ARIMA models using multivariate time series, ARMAX models i.e. ARIMA with explanatory variables etc

A good account on exponential smoothing methods is given in Makridakis *et al.* (1998). A practical treatment on ARIMA modeling along with several case studies can be found in Pankratz (1983). A reference book on ARIMA and related topics with a more rigorous theoretical flavour is by Box *et al.* (1994).

2. Time Series Components and Decomposition

An important step in analysing TS data is to consider the types of data patterns, so that the models most appropriate to those patterns can be utilized. Four types of time series components can be distinguished. They are

- (i) Horizontal – when data values fluctuate around a constant value
- (ii) Trend – when there is long term increase or decrease in the data
- (iii) Seasonal – when a series is influenced by seasonal factor and recurs on a regular periodic basis
- (iv) Cyclical – when the data exhibit rises and falls that are not of a fixed period

Note that many data series include combinations of the preceding patterns. After separating out the existing patterns in any time series data, the pattern that remains unidentifiable, form the 'random' or 'error' component. Time plot (data plotted over time) and seasonal plot (data plotted against individual seasons in which the data were observed) help in visualizing these patterns while exploring the data. A crude yet practical way of decomposing the original data (ignoring cyclical pattern) is to go for a seasonal decomposition either by assuming an additive or multiplicative model viz.

$$Y_t = T_t + S_t + E_t \text{ or } Y_t = T_t \cdot S_t \cdot E_t$$

where Y_t - Original TS data

T_t - Trend component

S_t - Seasonal component

E_t - Error/ Irregular component

If the magnitude of a TS varies with the level of the series then one has to go for a multiplicative model else an additive model. This decomposition may enable one to study the TS components separately or will allow workers to de-trend or to do seasonal adjustments if needed for further analysis.

3. Moving Averages and Exponential Smoothing Methods

(i) Simple moving averages

A moving average is simply a numerical average of the last N data points. There are prior MA, centered MA etc. in the TS literature. In general, the moving average at time t , taken over N periods, is given by

$$M_t^{[1]} = \frac{Y_t + Y_{t-1} + \dots + Y_{t-N+1}}{N}$$

where Y_t is the observed response at time t . Another way of stating the above equation is

$$M_t^{[1]} = M_{t-1}^{[1]} + (Y_t - Y_{t-N}) / N$$

At each successive time period the most recent observation is included and the farthest observation is excluded for computing the average. Hence the name ‘moving’ averages.

(ii) Double moving averages

The simple moving average is intended for data of constant and no trend nature. If the data have a linear or quadratic trend, the simple moving average will be misleading. In order to correct for the bias and develop an improved forecasting equation, the double moving average can be calculated. To calculate this, simply treat the moving averages $M_t^{[1]}$ over time as individual data points and obtain a moving average of these averages.

(iii) Simple Exponential smoothing (SES)

Let the time series data be denoted by Y_1, Y_2, \dots, Y_t . Suppose we wish to forecast the next value of our time series Y_{t+1} that is yet to be observed with forecast for Y_t denoted by F_t . Then the forecast F_{t+1} is based on weighting the most recent observation Y_t with a weight value α and weighting the most recent forecast F_t with a weight of $(1-\alpha)$ where α is a smoothing constant/weight between 0 and 1. Thus the forecast for the period $t+1$ is given by

$$F_{t+1} = F_t + \alpha(Y_t - F_t)$$

Note that the choice of α has considerable impact on the forecast. A large value of α (say 0.9) gives very little smoothing in the forecast, whereas a small value of α (say 0.1) gives considerable smoothing. Alternatively, one can choose α from a grid of values (say $\alpha=0.1, 0.2, \dots, 0.9$) and choose the value that yields the smallest MSE value.

If you expand the above model recursively then F_{t+1} will come out to be a function of α , past y_t values and F_1 . So, having known values of α and past values of y_t our point of concern relates to initializing the value of F_1 . One method of initialization is to use the first observed value Y_1 as the first forecast ($F_1=Y_1$) and then proceed. Another possibility would be to average the first four or five values in the data set and use this as the initial forecast. However, because the weight attached to this user-defined F_1 is minimal, its effect on F_{t+1} is negligible.

(iv) Double exponential smoothing (Holt)

This is to allow forecasting data with trends. The forecast for Holt’s linear exponential smoothing is found by having two more equations to SES model to deal with – one for level and one for trend. The smoothing parameters (weights) α and β can be chosen from a grid of values (say, each combination of $\alpha=0.1, 0.2, \dots, 0.9$ and $\beta=0.1, 0.2, \dots, 0.9$) and then select the combination of α and β which correspond to the lowest MSE.

In SPSS, the weights α and β can be chosen from a grid of values (say, each combination of $\alpha=0.1,0.2,\dots,0.9$ and $\beta=0.1,0.2,\dots,0.9$) and then select the combination of α and β which correspond to the lowest MSE.

Illustration: Consider Dataset-1 given in Appendix. Find the Holt’s exponential smoothing one-step-ahead forecasts for the period 2000-01 to 2003-04 by using SPSS and model built upon the years 1970-71 to 1999-2000 automatic values for initial and trend values and choosing grid of values between 0.1 to 0.9 with increment of 0.1 each time for both α and β (In SPSS, go to Analyse -> Time series -> Exponential smoothing model. In the pop up menu choose radio option button ‘Holt’; then choose the option “Parameters”. Also inside the option “Save” choose Predict through).

Also see Fig. (i) and SPSS Output I for details.

Note:- In SPSS, before proceeding to analyse TS data, periodicity has to be assigned to the data by defining “Dates”. For this, choose, Data -> Define Dates ->Cases Are: - defines the time interval used to generate dates.; First Case Is:- Defines the starting date value, which is assigned to the first case. Sequential values, based on the time interval, are assigned to subsequent cases.; Periodicity at higher level:- Indicates the repetitive cyclical variation, such as the number of months in a year or the number of days in a week. The value displayed indicates the maximum value you can enter. A new numeric variable is created for each component that is used to define the date.

(v) Triple exponential smoothing (Winters)

This method is recommended when seasonality exists in the time series data. This method is based on three smoothing equations – one for the level, one for trend, and one for seasonality. It is similar to Holt’s method, with one additional equation to deal with seasonality. In fact there are two different Winter’s methods depending on whether seasonality is modeled in an additive or multiplicative way.

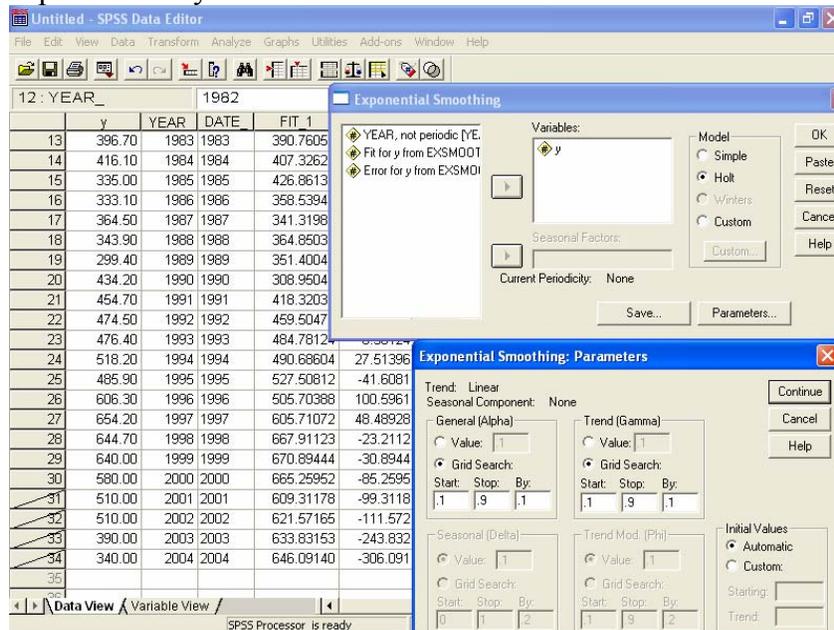


Fig (i) Forecasting using Holt’s exponential smoothing model in SPSS

SPSS Output (i) :- Forecasting using Holt's exponential smoothing model

→ ExSmooth

→ **Model Description**

Model Name	MOD_5	
Series	1	Y
Holt's Model	Trend	Linear
	Seasonality	None

Applying the model specifications from MOD_5

→ **Initial Smoothing State**

	y
Level	218.37069
Trend	12.25862

→ **Smallest Sums of Squared Errors**

Series	Model rank	Alpha (Level)	Gamma (Trend)	Sums of Squared Errors
Y	1	.80000	.10000	80272.18003
	2	.90000	.10000	80607.38830
	3	.70000	.10000	80765.87232
	4	.60000	.10000	82132.38969
	5	.50000	.10000	84727.41287
	6	.80000	.20000	85926.05272
	7	.70000	.20000	86229.65224
	8	.90000	.20000	86546.73944
	9	.60000	.20000	87393.88517
	10	.40000	.10000	89519.76179

→ **Smoothing Parameters**

Series	Alpha (Level)	Gamma (Trend)	Sums of Squared Errors	df error
Y	.80000	.10000	80272.18003	28

Shown here are the parameters with the smallest Sums of Squared Errors. These parameters are used to forecast.

4. Stationarity of a TS Process

A TS is said to be stationary if its underlying generating process is based on a constant mean and constant variance with its autocorrelation function (ACF) essentially constant through time. Thus, if we consider different subsets of a realization (time series 'sample') the different subsets will typically have means, variances and autocorrelation functions that do not differ significantly.

A statistical test for stationarity is the most widely used Dickey Fuller test. To carry out the test, estimate by OLS the regression model

$$y'_t = \phi y_{t-1} + b_1 y'_{t-2} + \dots + b_p y'_{t-p}$$

where y'_t denotes the differenced series ($y_t - y_{t-1}$). The number of terms in the regression, p , is usually set to be about 3. Then if ϕ is nearly zero the original series y_t needs differencing. And if $\phi < 0$ then y_t is already stationary.

5. Autocorrelation Functions

(i) Autocorrelation

Autocorrelation refers to the way the observations in a time series are related to each other and is measured by the simple correlation between current observation (Y_t) and observation from p periods before the current one (Y_{t-p}). That is for a given series Y_t , autocorrelation at lag p is the correlation between the pair (Y_t, Y_{t-p}) and is given by

$$r_p = \frac{\sum_{t=1}^{n-p} (Y_t - \bar{Y})(Y_{t+p} - \bar{Y})}{\sum_{t=1}^n (Y_t - \bar{Y})^2}$$

It ranges from -1 to $+1$. Box and Jenkins has suggested that maximum number of useful r_p are roughly $N/4$ where N is the number of periods upon which information on y_t is available.

(ii) Partial autocorrelation

Partial autocorrelations are used to measure the degree of association between y_t and y_{t-p} when the y -effects at other time lags $1, 2, 3, \dots, p-1$ are removed.

(iii) Autocorrelation function(ACF) and partial autocorrelation function(PACF)

Theoretical ACFs and PACFs (Autocorrelations versus lags) are available for the various models chosen (say, see Pankratz, 1984) for various values of orders of autoregressive and moving average components i.e. p and q . Thus compare the correlograms (plot of sample ACFs versus lags) obtained from the given TS data with these theoretical ACF/PACFs, to find a reasonably good match and tentatively select one or more ARIMA models. The general characteristics of theoretical ACFs and PACFs are as follows:- (here ‘spike’ represents the line at various lags in the plot with length equal to magnitude of autocorrelations)

Model	ACF	PACF
AR	Spikes decay towards zero	Spikes cutoff to zero
MA	Spikes cutoff to zero	Spikes decay to zero
ARMA	Spikes decay to zero	Spikes decay to zero

6. Description of ARIMA Representation

(i) ARIMA modeling

In general, an ARIMA model is characterized by the notation ARIMA (p,d,q) where, p, d and q denote orders of auto-regression, integration (differencing) and moving average respectively. In ARIMA parlance, TS is a linear function of past actual values and random shocks. For instance, given a time series process $\{y_t\}$, a first order auto-regressive process is denoted by ARIMA (1,0,0) or simply AR(1) and is given by

$$y_t = \mu + \phi_1 y_{t-1} + \varepsilon_t$$

and a first order moving average process is denoted by ARIMA (0,0,1) or simply MA(1) and is given by

$$y_t = \mu - \theta_1 \varepsilon_{t-1} + \varepsilon_t$$

Alternatively, the model ultimately derived, may be a mixture of these processes and of higher orders as well. Thus a stationary ARMA (p, q) process is defined by the equation

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \dots + \phi_p y_{t-p} - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} + \dots - \theta_q \varepsilon_{t-q} + \varepsilon_t$$

where ε_t 's are independently and normally distributed with zero mean and constant variance σ^2 for $t = 1, 2, \dots, n$. Note here that the values of p and q, in practice lie between 0 and 3. The degree of differencing of main variable y_t will be discussed in section 7 (i).

(ii) Seasonal ARIMA modeling

Identification of relevant models and inclusion of suitable seasonal variables are necessary for seasonal. The Seasonal ARIMA i.e. ARIMA (p,d,q) (P,D,Q)_s model is defined by

$$\phi_p(B) \varnothing_p(B^s) \nabla^d \nabla_s^D y_t = \Theta_Q(B^s) \theta_q(B) \varepsilon_t$$

where

$$\begin{aligned} \phi_p(B) &= 1 - \phi_1 B - \dots - \phi_p B^p, \quad \theta_q(B) = 1 - \theta_1 B - \dots - \theta_q B^q \\ \varnothing_p(B^s) &= 1 - \varnothing_1 B^s - \dots - \varnothing_p B^{sP}, \quad \Theta_Q(B^s) = 1 - \Theta_1 B^s - \dots - \Theta_Q B^{sQ} \end{aligned}$$

B is the backshift operator (i.e. $B y_t = y_{t-1}$, $B^2 y_t = y_{t-2}$ and so on), 's' the seasonal lag and ' ε_t ' a sequence of independent normal error variables with mean 0 and variance σ^2 . \varnothing 's and ϕ 's are respectively the seasonal and non-seasonal autoregressive parameters. Θ 's and θ 's are respectively seasonal and non-seasonal moving average parameters. p and q are orders of non-seasonal autoregression and moving average parameters respectively whereas P and Q are that of the seasonal auto regression and moving average parameters respectively. Also d and D denote non-seasonal and seasonal differences respectively.

7. The Art of ARIMA Model Building

(i) Identification

The foremost step in the process of modeling is to check for the stationarity of the series, as the estimation procedures are available only for stationary series. There are two kinds of stationarity, viz., stationarity in 'mean' and stationarity in 'variance'. A cursory look at the graph of the data and structure of autocorrelation and partial correlation coefficients may provide clues for the presence of stationarity. Another way of checking for stationarity is to fit a first order autoregressive model for the raw data and test whether the coefficient ' ϕ_1 ' is less than one. If the model is found to be non-stationary, stationarity could be achieved

mostly by differencing the series. Or go for a Dickey Fuller test(see section 4). Stationarity in variance could be achieved by some modes of transformation, say, log transformation. This is applicable for both seasonal and non-seasonal stationarity.

Thus, if 'X_t' denotes the original series, the non-seasonal difference of first order is

$$Y_t = X_t - X_{t-1}$$

followed by the seasonal differencing (if needed)

$$Z_t = Y_t - Y_{t-s} = (X_t - X_{t-1}) - (X_{t-s} - X_{t-s-1})$$

The next step in the identification process is to find the initial values for the orders of seasonal and non-seasonal parameters, p, q, and P, Q. They could be obtained by looking for significant autocorrelation and partial autocorrelation coefficients (see section 5 (iii)). Say, if second order auto correlation coefficient is significant, then an AR (2), or MA (2) or ARMA (2) model could be tried to start with. This is not a hard and fast rule, as sample autocorrelation coefficients are poor estimates of population autocorrelation coefficients. Still they can be used as initial values while the final models are achieved after going through the stages repeatedly.

Note that usually up to order 2 for p, d, or q are sufficient for developing a good model in practice.

(ii) Estimation

At the identification stage one or more models are tentatively chosen that seem to provide statistically adequate representations of the available data. Then we attempt to obtain precise estimates of parameters of the model by least squares as advocated by Box and Jenkins. Standard computer packages like SAS, SPSS etc. are available for finding the estimates of relevant parameters using iterative procedures. The methods of estimation are not discussed here for brevity.

(iii) Diagnostics

Different models can be obtained for various combinations of AR and MA individually and collectively. The best model is obtained with following diagnostics.

(a) Low Akaike Information Criteria (AIC)/ Bayesian Information Criteria (BIC)/ Schwarz-Bayesian Information Criteria (SBC)

AIC is given by $AIC = (-2 \log L + 2 m)$ where $m=p+ q+ P+ Q$ and L is the likelihood function. Since $-2 \log L$ is approximately equal to $\{n (1+\log 2\pi) + n \log \sigma^2\}$ where σ^2 is the model MSE, AIC can be written as $AIC=\{n (1+\log 2\pi) + n \log \sigma^2 + 2 m\}$ and because first term in this equation is a constant, it is usually omitted while comparing between models. As an alternative to AIC, sometimes SBC is also used which is given by $SBC = \log \sigma^2 + (m \log n) /n$.

(b) Plot of residual ACF

Once the appropriate ARIMA model has been fitted, one can examine the goodness of fit by means of plotting the ACF of residuals of the fitted model. If most of the sample autocorrelation coefficients of the residuals are within the limits $\pm 1.96 / \sqrt{N}$ where N is the

number of observations upon which the model is based then the residuals are white noise indicating that the model is a good fit.

(c) Non-significance of auto correlations of residuals via Portmonteau tests (Q-tests based on Chisquare statistics)-Box-Pierce or Ljung-Box texts

After tentative model has been fitted to the data, it is important to perform diagnostic checks to test the adequacy of the model and, if need be, to suggest potential improvements. One way to accomplish this is through the analysis of residuals. It has been found that it is effective to measure the overall adequacy of the chosen model by examining a quantity Q known as Box-Pierce statistic (a function of autocorrelations of residuals) whose approximate distribution is chi-square and is computed as follows:

$$Q = n \sum r^2(j)$$

where summation extends from 1 to k with k as the maximum lag considered, n is the number of observations in the series, r (j) is the estimated autocorrelation at lag j; k can be any positive integer and is usually around 20. Q follows Chi-square with (k-m₁) degrees of freedom where m₁ is the number of parameters estimated in the model. A modified Q statistic is the Ljung-box statistic which is given by

$$Q = n(n+2) \sum r^2(j) / (n-j)$$

The Q Statistic is compared to critical values from chi-square distribution. If model is correctly specified, residuals should be uncorrelated and Q should be small (the probability value should be large). A significant value indicates that the chosen model does not fit well.

All these stages require considerable care and work and they themselves are not exhaustive.

Illustration:

Consider Dataset 2 given in Appendix.

1. Draw time plot. Perform the following Dickey - Fuller test. Fit the model

$$y'_t = \phi y'_{t-1} + \phi_1 y'_{t-1} + \phi_2 y'_{t-2} + \phi_3 y'_{t-3}$$

with 'no intercept' and observe whether $\hat{\phi} \approx 0$ (i.e. data is non-stationary) or $\hat{\phi} < 0$ (i.e. data is stationary). Whether the data needs differencing?

2. By drawing correlograms identify the tentative values of p and q.
(In SPSS go to Graph -> Time series -> Autocorrelation)
3. Obtain parameter estimates of the model upon the years 1970-71 to 1999-2000 by identifying a series of ARIMA (p,d,q) models (p=0,1,2,3; d obtained in question 1; q = 0,1,2,3) also preserving parsimony that might be useful in describing the time series. Which of your models is the best according to their AIC values?
(In SPSS go to Analyse -> Time series -> ARIMA model)
4. For the models obtained in (3) & (4) perform separately diagnostic tests upon residuals using (i) Residual ACF (it) Box-Pierce Chi-square test.
5. Forecast for lead years 2000-01 to 2003-04.(Inside option Save -> 'Predict through')

See Fig. (ii) and SPSS Output (ii) for details.

Time-Series Analysis

The screenshot displays the SPSS Data Editor window with a data table and the ARIMA dialog box. The data table shows the following values for variable 'y':

Case Number	y	YEAR	DATE	y_1	FIT_1
20	143.00	1990	1990	54.00	80.463
21	117.00	1991	1991	-26.00	122.07
22	72.00	1992	1992	-45.00	112.66
23	124.00	1993	1993	52.00	119.27
24	180.00	1994	1994	56.00	121.28
25	154.00	1995	1995	-26.00	126.38
26	155.00	1996	1996	1.00	148.66
27	173.00	1997	1997	18.00	174.06
28	95.00	1998	1998	-78.00	168.15
29	139.00	1999	1999	44.00	140.53
30	162.00	2000	2000	23.00	157.67
31	100.00	2001	2001	-62.00	132.61
32	147.00	2002	2002	47.00	145.84
33	158.00	2003	2003	11.00	159.10
34	189.00	2004	2004	31.00	151.06

The ARIMA dialog box shows the following settings:

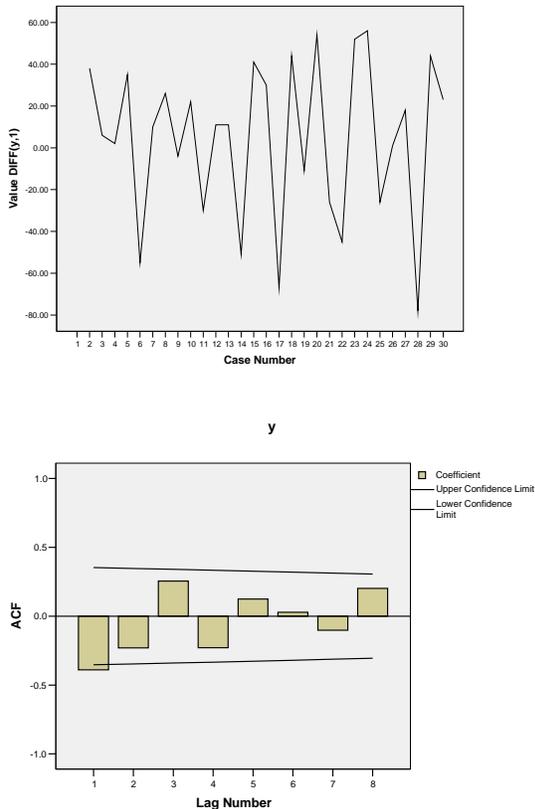
- Dependent: y
- Transform: None
- Model: Autoregressive p=2, Difference d=1, Moving Average q=0
- Include constant in model:

The ARIMA: Save dialog box shows the following settings:

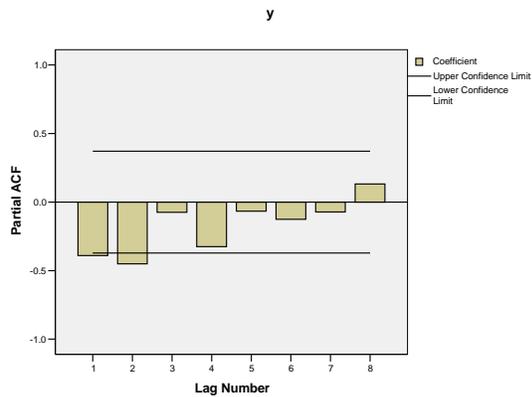
- Predict Cases: Predict through: Year: 2004
- % Confidence intervals: 95
- The Estimation Period is: Year 1971 -Year 2000

Fig (ii) Forecasting using ARIMA model in SPSS

SPSS Output (ii) :- Forecasting using ARIMA model



Time-Series Analysis



→ **Parameter Estimates**

		Estimate	Std Error	t	Approx Sig
Non-Seasonal Lags	AR1	-.613	.172	-3.558	.001
	AR2	-.499	.173	-2.880	.008
	Constant	3.169	2.819	1.124	.271

Melard's algorithm was used for estimation.

References

Box, G.E.P., Jenkins, G.M. and Reinsel, G.C. (1994). *Time series analysis : Forecasting and control*, Pearson Education, Delhi.

Makridakis, S., Wheelwright, S.C. and Hyndman, R.J. (1998). *Forecasting Methods and Applications*, 3rd Edition, John Wiley, New York.

Pankratz, A. (1983). *Forecasting with univariate Box – Jenkins models: concepts and cases*, John Wiley, New york.

Appendix: 34 years data relating to Cotton crop of India

Dataset-1 (Rajasthan state)				Dataset-2 (Maharashtra state)			
Year	Area	Year	Area	Year	Yield	Year	Yield
(in 1000 ha)		(in 1000 ha)		(in kg/ha)		(in kg/ha)	
1970-71	224.5	1987-88	343.9	1970-71	31	1987-88	100
1971-72	334.0	1988-89	299.4	1971-72	69	1988-89	89
1972-73	343.2	1989-90	434.2	1972-73	75	1989-90	143
1973-74	302.0	1990-91	454.7	1973-74	77	1990-91	117
1974-75	268.2	1991-92	474.5	1974-75	112	1991-92	72
1975-76	308.6	1992-93	476.4	1975-76	57	1992-93	124
1976-77	288.9	1993-94	518.2	1976-77	67	1993-94	180
1977-78	369.7	1994-95	485.9	1977-78	93	1994-95	154
1978-79	402.7	1995-96	606.3	1978-79	89	1995-96	155
1979-80	386.7	1996-97	654.2	1979-80	111	1996-97	173
1980-81	357.0	1997-98	644.7	1980-81	81	1997-98	95
1981-82	379.7	1998-99	640.0	1981-82	92	1998-99	139
1982-83	396.7	1999-00	580.0	1982-83	103	1999-00	162
1983-84	416.1	2000-01	510.0	1983-84	52	2000-01	100
1984-85	335.0	2001-02	510.0	1984-85	93	2001-02	147
1985-86	333.1	2002-03	390.0	1985-86	123	2002-03	158
1986-87	364.5	2003-04	340.0	1986-87	56	2003-04	189