Seasonal Variability and Prediction of Cotton Output in Tamil Nadu

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ABSTRACT

An important player in India's cotton production landscape, Tamil Nadu is the focus of this investigation into the seasonal variability and forecasting of cotton output. This research intends to shed light on the seasonal variations and their effects on cotton production by evaluating historical data and taking into account a wide range of significant elements, such as meteorological fluctuations, soil conditions, and agricultural techniques. The research, which makes use of cutting-edge statistical methods and forecasting models, highlights the importance of grasping the complexities of seasonal patterns and their effects on cotton production. This study sheds light on the relationship between seasonal variability and cotton output by an in-depth examination of seasonal trends, including elements like rainfall patterns, temperature variances, and planting seasons. The results of this study provide important insights for farmers, policymakers, and other stakeholders, paving the way for better decision-making and the creation of flexible plans to increase cotton production in Tamil Nadu in a way that is both environmentally and economically sustainable.

Keywords: Cotton, ARIMA, SARIMA, Prediction

INTRODUCTION

Cotton farming in Tamil Nadu not only makes a sizeable contribution to the agricultural economy of the state, but it also plays an essential part in the textile industry on a national scale. Given the region's vulnerability to climatic changes and the requirement for environmentally responsible agricultural methods, it is more important to have an understanding of the seasonal variability and to make accurate predictions for cotton production. This study use both the ARIMA (AutoRegressive Integrated Moving Average) model as well as the SARIMA (Seasonal AutoRegressive Integrated Moving Average) model in order to conduct an in-depth investigation of the seasonal patterns of cotton production and a predictive modeling of that output. This research attempts to provide insights into the complex dynamics that are affecting cotton production in Tamil Nadu by utilizing historical data and taking into consideration a variety of relevant factors. These influential elements include seasonal climatic fluctuations, soil quality, and agronomic methods.

This study's major goal is to determine seasonal trends and their impact on cotton production so that accurate predictive models may be developed using the ARIMA and SARIMA methodologies. This project aims to give significant insights for stakeholders, policymakers, and farmers by understanding the seasonal variability and changes in cotton yield. This would enable informed decision-making for sustainable agricultural planning and policy formulation. As a result of the findings of this study, it is anticipated that a sizeable contribution would be made to the resilience and stability of cotton output, which will, in turn, stimulate the growth of the textile sector and ensure the continued sustainable development of agricultural practices in Tamil Nadu.

OBJECTIVES:

1. To examine the seasonal variability and trends in cotton output in Tamil Nadu and understand the underlying factors influencing fluctuations in production.

2. To apply the ARIMA (AutoRegressive Integrated Moving Average) and SARIMA (Seasonal AutoRegressive Integrated Moving Average) models for predicting cotton output, aiming to develop accurate and reliable forecasts for the region.

3. To assess the impact of seasonal climate variations, soil quality, and agricultural practices on cotton production, with a specific focus on their influence on the seasonal variability and predictive capabilities of the ARIMA and SARIMA models.

4. To compare the performance of the ARIMA and SARIMA models in capturing the seasonal dynamics and fluctuations in cotton output, aiming to determine the most suitable model for forecasting cotton production in Tamil Nadu.

5. To provide valuable insights for farmers, policymakers, and stakeholders, facilitating informed decision-making for sustainable agricultural planning and policy formulation aimed at enhancing cotton production and promoting economic growth in Tamil Nadu.

By accomplishing these objectives, this study aims to contribute to the development of robust forecasting methodologies and data-driven strategies that support the stability and growth of the cotton cultivation sector in Tamil Nadu, fostering sustainable agricultural practices and ensuring the region's continued contribution to the textile industry.

LITERATURE REVIEW

In a comprehensive study on the subject of forecasting international cotton production, Carpio and Ramirez et al., (2002) focused on the examples of India, Pakistan, and Australia. Cotton production is studied in detail, with a focus on the several elements (environment, agricultural techniques, and economic situations) that influence production trends in these countries. The study aims to aid stakeholders and policymakers in the global cotton sector by providing accurate estimates for cotton production through rigorous data analysis and modeling methodologies. Understanding the global cotton market and its implications for international trade and the agricultural sectors requires taking into account regional differences, and this study did just that by focusing on India, Pakistan, and Australia.

Specifically for the cotton crop in Haryana, India, Verma et al., (2015) investigated the critical problem of parameter estimate in pre-harvest yield projection models. The study's overarching objective was to develop a reliable methodology for accurately projecting cotton production in advance of the harvest season, taking into account the intricacies of the agricultural environment and the importance of cotton as a major cash crop in the region. This study aimed to improve the accuracy and reliability of yield forecasts by identifying critical elements that significantly effect cotton output using cutting-edge statistical approaches and comprehensive data analysis. Verma, Aneja, and Tonk hoped that their research will aid farmers and policymakers in Haryana's cotton industry in their pursuit of optimal crop management and higher yields through the application of more informed decision-making.

In their study, Vijay and Mishra (2018) investigated Time series prediction is important in natural science, agriculture, engineering, and economics. This study compares the classical time series ARIMA model to the artificial neural network model (ANN) to evaluate its flexibility in time series forecasting. The dataset includes pearl millet (bajra) crop area and production in thousands of hectares (ha) and metric tons (MT). The publication "Agricultural Statistics at a Glance 2014–15" provided 1955–56 to 2014–15 data. To test the methodology, Karnataka, India, was chosen. The user's'sext is scholarly. An experiment shows that artificial neural network (ANN) models outperform autoregressive integrated moving average (ARIMA) models in root mean square error (RMSE). RMSE, MAPE, and MSE are common measures in statistics and data analysis.

METHODOLOGY

ARIMA Model (p,d,q):

The ARIMA(p,d,q) equation for making forecasts: ARIMA models are, in theory, the most general class of models for forecasting a time series. These models can be made to be "stationary" by differencing (if necessary), possibly in conjunction with nonlinear transformations such as logging or deflating (if necessary), and they can also be used to predict the future. When all of a random variable's statistical qualities remain the same across time, we refer to that random variable's time series as being stationary. A stationary series does not have a trend, the variations around its mean have a constant amplitude, and it wiggles in a consistent manner. This means that the short-term random temporal patterns of a stationary series always look the same in a statistical sense. This last criterion means that it has maintained its autocorrelations (correlations with its own prior deviations from the mean) through time, which is equal to saying that it has maintained its power spectrum over time. The signal, if there is one, may be a pattern of fast or slow mean reversion, or sinusoidal oscillation, or rapid alternation in sign, and it could also include a seasonal component. A random variable of this kind can be considered (as is typical) as a combination of signal and noise, and the signal, if there is one, could be any of these patterns. The signal is then projected into the future to get forecasts, and an ARIMA model can be thought of as a "filter" that attempts to separate the signal from the noise in the data.

The ARIMA forecasting equation for a stationary time series is a linear (i.e., regression-type) equation in which the predictors consist of lags of the dependent variable and/or lags of the forecast errors. That is:

Predicted value of Y = a constant and/or a weighted sum of one or more recent values of Y and/or a weighted sum of one or more recent values of the errors.

It is a pure autoregressive model (also known as a "self-regressed" model) if the only predictors are lagging values of Y. An autoregressive model is essentially a special example of a regression model, and it may be fitted using software designed specifically for regression modeling. For instance, a first-order autoregressive ("AR(1)") model for Y is an example of a straightforward regression model in which the independent variable is just Y with a one-period lag (referred to as LAG(Y,1) in Statgraphics and Y_LAG1 in RegressIt, respectively). Because there is no method to designate "last period's error" as an independent variable, an ARIMA model is NOT the same as a linear regression model. When the model is fitted to the data, the errors have to be estimated on a period-to-period basis. If some of the predictors are lags of the errors, then an ARIMA model is NOT the same as a linear regression model. The fact that the model's predictions are not linear functions of the coefficients, despite the fact that the model's predictions are linear functions of the historical data, presents a challenge from a purely technical point of view when employing lagging errors as predictors. Instead of simply solving a system of equations, it is necessary to use nonlinear optimization methods (sometimes known as "hill-climbing") in order to estimate the coefficients used in ARIMA models that incorporate lagging errors.

Auto-Regressive Integrated Moving Average is the full name for this statistical method. Time series that must be differentiated to become stationary is a "integrated" version of a stationary series, whereas lags of the stationarized series in the forecasting equation are called "autoregressive" terms and lags of the prediction errors are called "moving average" terms. Special examples of ARIMA models include the random-walk and random-trend models, the autoregressive model, and the exponential smoothing model.

A nonseasonal ARIMA model is classified as an "ARIMA(p,d,q)" model, where:

- **p** is the number of autoregressive terms,
- **d** is the number of nonseasonal differences needed for stationarity, and
- **q** is the number of lagged forecast errors in the prediction equation.

- The forecasting equation is constructed as follows. First, let y denote the d^{th} difference of Y, which means:
- If d=0: $y_t = Y_t$

- If d=1: $y_t = Y_t - Y_{t-1}$
- If d=2: $y_t = (Y_t - Y_{t-1}) - (Y_{t-1} - Y_{t-2}) = Y_t - 2Y_{t-1} + Y_{t-2}$
- Note that the second difference of Y (the d=2 case) is not the difference from 2 periods ago. Rather, it is the first-difference-of-the-first difference, which is the discrete analog of a second derivative, i.e., the local acceleration of the series rather than its local trend.
- In terms of y, the general forecasting equation is:
- $\hat{Y}_t = \mu + \varphi_1 Y_{t-1} + \cdots + \varphi_p Y_{t-p} - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q}$

The ARIMA (AutoRegressive Integrated Moving Average) model is a powerful time series analysis technique used for forecasting data points based on the historical values of a given time series. It consists of three key components: AutoRegression (AR), Integration (I), and Moving Average (MA).

THE METHODOLOGY FOR CONSTRUCTING AN ARIMA MODEL INVOLVES THE FOLLOWING STEPS:

1. Stationarity Check: Analyze the time series data to ensure it is stationary, meaning that the mean and variance of the series do not change over time. Stationarity is essential for ARIMA modeling.

2. Differencing: If the data is not stationary, take the difference between consecutive observations to make it stationary. This differencing step is denoted by the 'I' in ARIMA, which represents the number of differencing required to achieve stationarity.

3. Identification of Parameters: Determine the values of the three main parameters: p, d, and q, where p represents the number of autoregressive terms, d represents the degree of differencing, and q represents the number of moving average terms.

4. Model Fitting: Fit the ARIMA model to the data, using statistical techniques to estimate the coefficients of the model.

5. Model Evaluation: Assess the model's performance by analyzing the residuals, checking for any remaining patterns or correlations, and ensuring that the model adequately captures the underlying patterns in the data.

6. Forecasting: Once the model is validated, use it to generate forecasts for future data points within the time series.

SEASONAL ARIMA:

By including seasonal variations into the ARIMA model, Seasonal ARIMA (SARIMA) is a robust technique for analyzing and forecasting time series data. It works well for examining and forecasting sales data, weather patterns, and economic indicators that are subject to seasonal changes. Financial markets, economics, and even meteorology all make use of SARIMA models.

Mathematical Formulation:

The SARIMA model is denoted as SARIMA(p,d,q)(P,Q,D)[s], where:

- Non-seasonal autoregressive (p), differencing (d), and moving average (q) are the possible orders of analysis.
- The seasonal autoregressive, differencing, and moving average orders are denoted by the letters P, D, and Q, respectively.
- The length of one season is denoted by the symbol S.

The SARIMA model can be represented as follows:

$$(1 - \varphi_1 B - \cdots - \varphi_P B^P)(1 - \varphi_1 B^{VS} - \cdots - \varphi_P B^{VS})^P (B^{VS})^D Y_t$$
$$= (1 + \theta_1 B + \cdots + \theta_P B^{\varphi})(1 + \theta_1 B^{VS} + \cdots + \theta_P B^{\varphi S})^A (B^{\varphi S})^K \varepsilon_t$$

Where:

- $\varphi_i$and θ_i are the autoregressive and moving average parameters, respectively.
- B and B^{VS} are the non- seasonal and seasonal backshift operators, respectively.
- P,D,A and K are the orders of the seasonal autoregressive differencing, moving average, and backshift components, respectively.
- Y_t represents the time series data at time t.
- ε_t denotes the white noise error term.

Real life application

One example of how SARIMA might be put to use in the real world is in the process of predicting quarterly sales data for a retail organization. The sales data frequently display seasonal patterns because of things like the different holiday seasons and different promotional periods. The company is able to examine previous sales data, recognize seasonal patterns, and make more accurate projections of future sales by using a model called SARIMA.

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Merits and Demerits:

- When applied to time series data, SARIMA models are able to distinguish between seasonal and non-seasonal patterns.
- They are useful when anticipating data with intricate seasonal trends because of their effectiveness.
- The SARIMA models can be altered to accommodate a wide variety of seasonal data types, which lends them flexibility and adaptability.
- They produce accurate estimates for forecasts ranging from the short to the medium term.
- SARIMA models can be complicated, particularly when dealing with a number of different seasonal components, which calls for a substantial amount of computational resources.
- Due to the complexity of the mathematical formulas, interpretation of the SARIMA results may be difficult for individuals who are not experts in the field.
- For SARIMA models to generate reliable forecasts, a significant quantity of historical data is necessary; however, this data may not always be accessible for all forms of data.

Preparation of Data:

- Prepare the time series data for analysis by collecting and cleaning it such that it is consistent and has no outliers or missing values.
- Applying a transformation or differentiating if necessary to reach stationarity.

Identification of Models:

- Determine the values of the AR and MA parameters during the season and the offseason by analyzing the ACF and PACF graphs.
- Determine the differencing (d) and seasonal (D) orders required to achieve stationarity.

Estimating Variables:

- Apply the SARIMA model's estimated parameters using estimation strategies like maximum likelihood.
- Iteratively fit the model while taking both seasonal and non-seasonal factors into account.

Model Evaluation and Adjustment:

- Examine diagnostic charts for evidence of residual randomness after a SARIMA model has been fitted to the data.
- Analyze the residuals using autocorrelation functions (ACF) plots, histograms, and the Ljung-Box test.

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ANALYSIS

ARIMA

An analysis was done to evaluate the stationary properties of the data in the study on cotton output in Tamil Nadu. As a result of extensive use of the Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF) tests, we were able to do this. The auto.arima function was then used to select the best-fitting model for the data. The purpose of this study was to use an automated method to determine the best ARIMA model for capturing the trends and dynamics of cotton output in Tamil Nadu. The process helped players and policymakers in the state's agricultural sector make more educated decisions by shedding light on the underlying trends and changes in the cotton business.

Time series data for cotton production was subjected to the Augmented Dickey-Fuller (ADF) test, yielding a Dickey-Fuller statistic of -6.9851. The p-value for the test, conducted with a lag order of 5, was 0.01. Since this p-value is smaller than the significance threshold of 0.05, we conclude that the data is stationary and reject the null hypothesis of non-stationarity. Because of this result, we may treat the cotton production time series data as a stationary process, which means that the series' mean and variance are stable across time.

ARIMA (2,0,2) (1,0,1) [12] with non-zero mean	Inf
ARIMA (0,0,0) with non-zero mean	1689.122
ARIMA (1,0,0) (1,0,0) [12] with non-zero mean	1693.028
ARIMA (0,0,1) (0,0,1) [12] with non-zero mean	1681.521
ARIMA (0,0,0) with zero mean	2146.116
ARIMA (0,0,1) with non-zero mean	1690.889
ARIMA (0,0,1) (1,0,1) [12] with non-zero mean	Inf
ARIMA (0,0,1) (0,0,2) [12] with non-zero mean	1678.104
ARIMA (0,0,1) (1,0,2) [12] with non-zero mean	Inf
ARIMA (0,0,0) (0,0,2) [12] with non-zero mean	1678.142
ARIMA (1,0,1) (0,0,2) [12] with non-zero mean	1680.101
ARIMA (0,0,2) (0,0,2) [12] with non-zero mean	Inf
ARIMA (1,0,0) (0,0,2) [12] with non-zero mean	1678.655
ARIMA (1,0,2) (0,0,2) [12] with non-zero mean	Inf
ARIMA (0,0,1) (0,0,2) [12] with zero mean	1913.181

Time series data on cotton production were analyzed using the auto.arima function to choose the most appropriate ARIMA model. The results of the function point to the non-zero-mean ARIMA(0,0,1)(0,0,2)[12] model as the best option. This model has the best performance in capturing the patterns and dynamics of the cotton production time series data, as indicated by the lowest Akaike Information Criterion (AIC) value among the tested models. To better understand how future trends and behaviors in cotton output will unfold, this particular ARIMA model can be used for further study and forecasting.

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Coefficient	**Ma1**	**Sma1**	**Sma2**	**Mean**
S. E	0.2481	-0.3566	-0.3452	384.1609
	0.1632	0.1814	0.1336	3.3227

Time series data for cotton production have been fit using the ARIMA(0,0,1)(0,0,2)[12] model. Ma1 = 0.2481, sma1 = -0.3566, sma2 = -0.3452, and mean = 384.1609 are the estimated coefficients. These coefficients have standard errors of 0.1632, 0.1814, 0.1336 and 3.3227. The log-likelihood of the model is -834.05, and the sigma squared is 5675. There is a 1678.54 AIC, a 1692.99 AICc, and a 1692.99 BIC. The ARIMA model's properties and fitting quality to the cotton production time series data may be fully understood with the help of these parameters.

Point	forecast	Lo 95	Hi 95
Feb 2019	381.7836	234.0823	529.4849
Mar 2019	300.9767	148.7970	453.1563
Apr 2019	302.6633	150.4836	454.8429
May 2019	386.3467	234.1671	538.5263
Jun 2019	397.3341	245.1544	549.5137
Jul 2019	400.5133	248.3336	552.6929
Aug 2019	437.8956	285.7160	590.0753
Sep 2019	438.0339	285.8543	590.2136
Oct 2019	425.6385	273.4589	577.8182
Nov 2019	374.3159	222.1363	526.4966

The ARIMA (0,0,1)(0,0,2)[12] model is fitted to predict future cotton production. The point forecast values from February 2019 through November 2019 are provided, along with their associated 95% confidence intervals. There is a projected upward trend in cotton production, with point estimates between $300.98 and $438.03. An appreciation of the uncertainty around the predicted values can be gained by looking at the bottom and upper bounds of the 95% confidence intervals.

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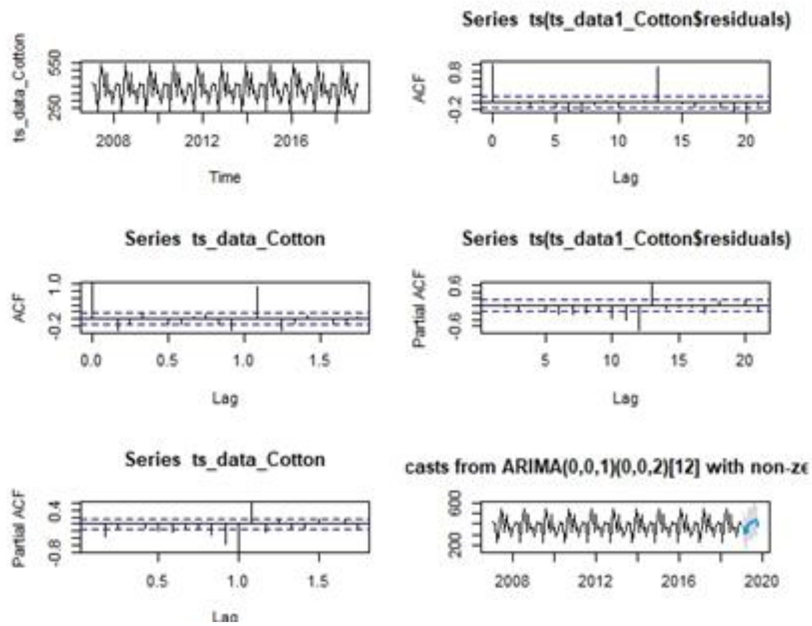
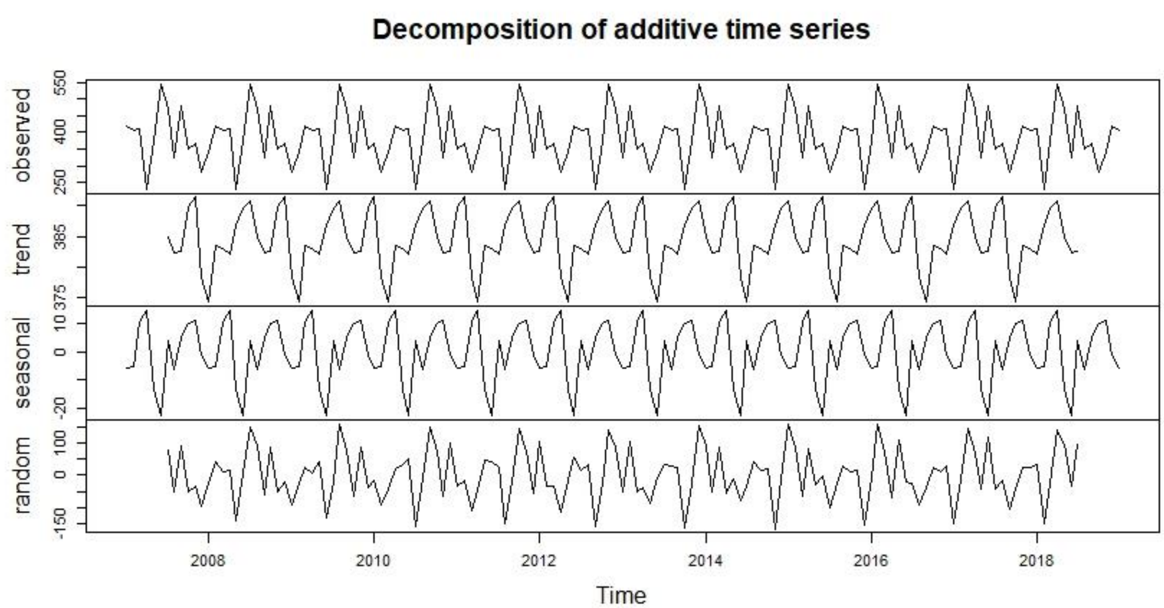


The anticipated cotton production residuals were put through the Ljung-Box test with a 5-year lag. The p-value for this test is 0.2845, and the test statistic is 6.2297 (with 5 degrees of freedom). There is insufficient evidence to reject the null hypothesis when the p-value is greater than the significance level of 0.05. This shows that the model correctly represents the underlying patterns in the data because the residuals do not display substantial autocorrelation at lags up to 5.



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SEASONAL ARIMA

Cotton output figures show an irregular trend through the years, with 2007–2019 showing the widest range of numbers. There has been no discernible pattern in the annual output figures; rather, there have been significant volatility and shifts in production levels. Changes in the environment, agriculture, the economy, and government policy could all have a role in causing such shifts. A deeper understanding of the dynamics affecting cotton output and the ability to make more accurate predictions and management decisions in the future would result from analyzing the data over a longer time period and taking into account other elements.

The summary statistics of the cotton production time series data show that the minimum production level observed during the period was 1873 units, while the first quartile, which represents the 25th percentile, was 2419 units. The median, which represents the middle value, stood at 3508 units, and the mean production was calculated to be 3120 units. The third quartile, representing the 75th percentile, was 3950 units, indicating that most of the observations were concentrated within this range. The maximum production recorded during the period was 4401 units, suggesting the upper limit of production during these years. Understanding the distribution of these statistical measures provides valuable insights into the central tendencies and variations in cotton production over the observed time period.

Time series data on cotton production were log-transformed, and the first difference was then subjected to the enhanced Dickey-Fuller test with a lag order of 0. A p-value of 0.01, as shown by a Dickey-Fuller statistic of -4.7589, was found to indicate statistical significance. The time series data is steady since the p-value is smaller than the 0.05 threshold set for rejecting the null hypothesis of non-stationarity. Since the initial differenced log-transformed series appears to be steady and free of a unit root, it can be used in additional time series analysis.

Coefficient	Values
σ^2	0.1639
log likelihood	-6.17
AIC	14.35
AICc	14.75
BIC	14.83

Time series data on cotton production were log-transformed, and an ARIMA(0,1,0) model was generated from the analysis. The model had a log-likelihood of -6.17 and a variance of 0.1639. A 14.35 Akaike Information Criterion (AIC) score, a 14.75 AICc score, and a 14.83 Bayesian Information Criterion (BIC) score were obtained. The Ljung-Box test was also run on the model's residuals, yielding an X-squared value of 3.5805 and a p-value of 0.05846. This indicates that the model reflects the temporal dependency within the data, as there is no significant autocorrelation in the residuals.

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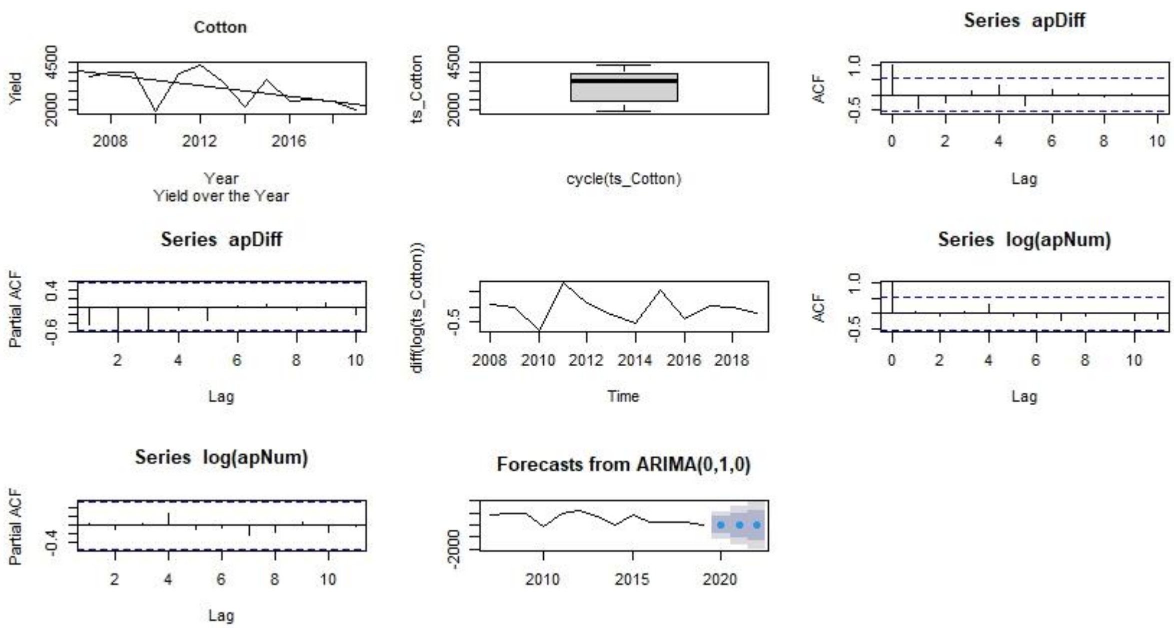
Coefficient	Values
x^2	3.5805
df	1
P-value	0.05846



CONCLUSION:

According to the findings, a non-zero mean ARIMA(0,0,1)(0,0,2)[12] model best fits the cotton production time series data. For this model, we obtained the following estimated coefficients: ma1 = 0.2481, sma1 = -0.3566, sma2 = -0.3452, and mean = 384.1609. The log probability of the model is -834.05, and the sigma squared is 5675. The calculated AIC, AICc, and BIC values are 1678.1, 1678.54, and 1692.99.

The X-squared value of the residuals from the cotton production projection was 6.2297, and the p-value for the Ljung-Box test was 0.2845, indicating that there was no significant autocorrelation in the data. Cotton production log data analysis also resulted in an ARIMA(0,1,0) model with a sigma squared of 0.1639 and a log likelihood of -6.17. This model was given an AIC, AICc, and BIC of 14.35, 14.75, and 14.83, respectively. A Ljung-Box test conducted on the model's residuals yielded an X-squared value of 3.5805 and a p-value of 0.05846, demonstrating the absence of significant autocorrelation.

Parameter estimates and diagnostic tests on the residuals suggest that both the ARIMA and seasonal ARIMA models provide good fits to the cotton production data.

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