Time Series Models for Oil Seeds Yield Prediction in Tamil Nadu

K. Murali[1] , K. Sreenivasulu[2] , M. Pushpalatha[3] , S. Hari Prasad[4] , G.Mokesh Rayalu[5]**

[1]Academic Consultant, Dept. of Statistics, S.V University, Tirupati.
[2]Lecturer in Statistics, SPW Degree College , Tirupati
[3]Lecturer in Statistics, SPW Degree College , Tirupati
[4]Lecturer in Statistics, Govt. Degree College,Kodur(RS)
Corresponding Author **
[5]Assistant Professor, Sr Grade 1 ,Department of Mathematics, School of Advanced Sciences,VIT,Vellore
mokesh.g@gmail.com

ABSTRACT

The primary objective of this research project is to investigate the utilization of time series models in the prediction of oilseed yield in the region of Tamil Nadu, India. The study explores the complex dynamics and relevant elements that impact oilseed farming, highlighting the importance of oilseed production within the agricultural landscape of the region. This study attempts to establish a precise prediction framework for projecting future oilseed yields by utilizing the sophisticated ARIMA (AutoRegressive Integrated Moving Average) and SARIMA (Seasonal AutoRegressive Integrated Moving Average) models. By utilizing historical data and conducting an analysis of seasonal patterns, this study aims to elucidate the temporal variability and fundamental trends that influence oilseed production in the region of Tamil Nadu. The findings obtained from this research will provide valuable inputs for farmers, policymakers, and stakeholders, enabling them to make well-informed decisions. This, in turn, will support the implementation of sustainable agricultural practices and the development of successful strategies to promote the long-term growth and stability of the oilseed industry in the region.

Keywords: Oil Seeds, ARIMA, SARIMA, Forecasting

INTRODUCTION

The cultivation of oilseeds is an essential part of Tamil Nadu's agricultural industry; as a result, the state has played an important part in both the expansion of the regional economy and the development of the edible oil market. The cultivation of oilseeds presents a number of obstacles resulting from fluctuations in climate, the quality of the soil, and agronomic techniques. As a result, the development of reliable prediction models is required in order to maximize crop production and ensure the agricultural sector's long-term viability. Both the ARIMA (AutoRegressive Integrated Moving Average) and SARIMA (Seasonal AutoRegressive Integrated Moving Average) models are incorporated into this investigation of time series models for oilseed yield prediction in Tamil Nadu. This research is to develop an efficient framework for predicting future oilseed yields in the region by examining historical data and taking into consideration influential aspects such as seasonal climatic changes, soil fertility, and agricultural techniques. The goal of this research is to develop an effective framework.

The application of the ARIMA and SARIMA models is the primary purpose of this investigation. These models are intended to be used to accurately capture the temporal patterns and fluctuations in oilseed production. This research aims to provide valuable insights for farmers, policymakers, and stakeholders by examining the temporal dynamics of oilseed yield variability and identifying the key factors influencing that variability. This will enable informed decision-making for sustainable agricultural practices and policy formulation. It is anticipated that the findings of this study would contribute to the improvement of oilseed farming, which will promote agricultural resilience and ensure the sustained expansion and stability of the oilseed sector in Tamil Nadu.

OBJECTIVES:

1. To analyze historical time series data of oilseed yield in Tamil Nadu and identify the underlying trends and patterns affecting yield fluctuations.

2. To apply the ARIMA (AutoRegressive Integrated Moving Average) and SARIMA (Seasonal AutoRegressive Integrated Moving Average) models for oilseed yield prediction, aiming to develop accurate and reliable forecasts for oilseed production in the region.

3. To assess the impact of seasonal climate variations, soil quality, and agricultural practices on oilseed yield, focusing on their influence on the predictive capabilities of the ARIMA and SARIMA models.

4. To compare the performance of the ARIMA and SARIMA models in capturing the temporal dynamics and fluctuations in oilseed yield, aiming to determine the most suitable model for forecasting oilseed 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 that supports the growth and stability of the oilseed cultivation sector in Tamil Nadu.

By achieving these objectives, this study aims to contribute to the development of effective strategies for enhancing oilseed production, promoting agricultural sustainability, and ensuring food security in the region of Tamil Nadu.

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LITERATURE REVIEW

Predicting the pricing of oilseeds, and more specifically groundnut in the Indian market, is the primary subject of Darekar and Reddy's (2017) research paper. The research uses advanced forecasting methods to examine the complex dynamics of oilseed price changes in an effort to identify recurrent patterns and emerging market trends. The study analyzes groundnut prices over time to determine what factors, such as demand and supply, international market trends, and domestic economic indicators, have played a role in driving those prices. Stakeholders in the oilseed industry may benefit from the study's findings because of the insights and prediction models it provides for production planning, risk management, and market positioning.

Saranyadevi and Mohideen (2021) conduct research on groundnut production forecasts using a hybrid technique that combines ARIMA models with a neural network. The study's overarching goal is to give a thorough understanding of the underlying elements impacting groundnut farming, including agricultural methods, climatic fluctuations, and socio-economic concerns, with the hope of improving the accuracy of production projections. The research contributes to the development of strong forecasting tools that can help policymakers, farmers, and industry players make educated decisions about crop planning, resource allocation, and market positioning by integrating advanced statistical models and machine learning algorithms. The results of this research highlight the value of data-driven methods for improving the precision and consistency of agricultural production projections, which in turn promotes sustainable practices and efficient resource management in the groundnut cultivation industry.

Mitra et al. (2017) dedicate their work to improving the accuracy of forecasting oilseeds and pulses production in India by creating hierarchical time-series models. The authors hope that their research will give a holistic framework for understanding the complex dynamics and seasonal fluctuations of oilseed and pulse production in agriculture. The researchers use hierarchical modeling techniques to stress the significance of taking into account several tiers of data, such as geographical differences, climate factors, and interdependencies in the production of various agricultural products. The study contributes to the advancement of forecasting methodologies in the agriculture sector through its novel approach that integrates hierarchical time-series analysis, allowing policymakers and stakeholders to make educated decisions regarding crop management, market planning, and supply chain optimization. The study demonstrates the significance of hierarchical models in improving the precision and consistency of output forecasts, which in turn promotes sustainable agricultural practices and expands India's oilseeds and pulses production industry.

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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.

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- 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.

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.

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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.

Analysis:

ARIMA

Time series data for oilseeds were subjected to the Augmented Dickey-Fuller (ADF) test, which yielded a test statistic of -7.3591 and a p-value of 0.01, respectively. Based on these findings, we decided to adopt the alternative hypothesis of stationarity and reject the null of non-stationarity. This suggests that there is no discernible trend or seasonality in the data for oilseeds across time, and hence the series is stable. In order to create reliable forecasting models and make well-informed judgments in the agriculture industry, the ADF test is an indispensable instrument of time series analysis.

ARIMA (2,0,2) (1,0,1) [12] with non-zero mean	Inf
ARIMA (0,0,0) with non-zero mean	2078.645
ARIMA (1,0,0) (1,0,0) [12] with non-zero mean	2081.253
ARIMA (0,0,1) (0,0,1) [12] with non-zero mean	2081.481
ARIMA (0,0,0) with zero mean	2650.279
ARIMA (0,0,0) (1,0,0) [12] with non-zero mean	2079.679
ARIMA (0,0,0) (0,0,1) [12] with non-zero mean	2079.739
ARIMA (0,0,0) (1,0,1) [12] with non-zero mean	2081.679
ARIMA (1,0,0) with non-zero mean	2079.363
ARIMA (0,0,1) with non-zero mean	2079.482
ARIMA (1,0,1) with non-zero mean	2081.361

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Time series data for oilseeds were analyzed using the auto.arima function with the AIC as the information criteria. Several possible ARIMA models with different parameters were generated by the tool. The study revealed that ARIMA(0,0,0) with a non-zero mean provided the best fit, implying that differencing was unnecessary for the time series data. With an AIC of 2078.645, it was determined that this ARIMA setup best captured the patterns and fluctuations present in the oilseeds data. Using this selected model, oilseed producers and distributors will be better able to foresee potential developments and make educated choices.

Coefficients	values
Mean	2215.86
s.e.	25.7039
sigma^2	96465
log likelihood	-1037.3
AIC	2078.64
AICc	2078.73
BIC	2084.6

The oilseeds time series data fit well inside the ARIMA(0,0,0) model with a non-zero mean. The average level of the series, as determined by the model coefficients, was found to be 2215.8621. It was determined that the mean standard deviation was 25.7039. In addition, the log-likelihood of the model was calculated to be -1037.32 and the sigma squared value was discovered to be 96465. After running the numbers, we found that the BIC was 2084.6, the AIC was 2078.64, and the AICc was 2078.73. Collectively, these parameters evaluate the model's capacity to describe and anticipate the underlying trends in the oilseeds time series data and hence determine its goodness of fit.

Point	Forecast	Lo 95	Hi 95
Feb 2019	2215.862	1607.119	2824.605
Mar 2019	2215.862	1607.119	2824.605
Apr 2019	2215.862	1607.119	2824.605
May 2019	2215.862	1607.119	2824.605
Jun 2019	2215.862	1607.119	2824.605
Jul 2019	2215.862	1607.119	2824.605
Aug 2019	2215.862	1607.119	2824.605
Sep 2019	2215.862	1607.119	2824.605
Oct 2019	2215.862	1607.119	2824.605
Nov 2019	2215.862	1607.119	2824.605

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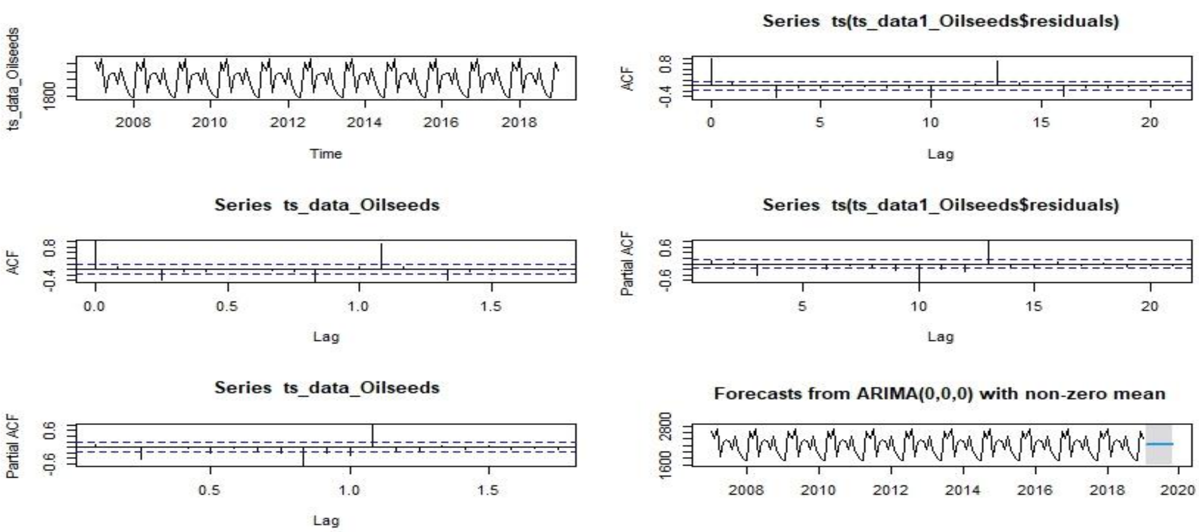
The projected values for oilseed output indicate a steady upward trend, with a point estimate of 2215.862 for each month in 2019, beginning in February and continuing through November. The range of values that represent the lower and upper boundaries of a confidence interval with a significance level of 95% is from 1607.119 to 2824.605. The players in the oilseeds sector can use these projections to better plan their production, distribution, and pricing plans for the months ahead, thanks to the information provided. The anticipated values help assist informed decision-making processes by providing an estimation of the expected production levels. This might potentially lead to more effective resource allocation and enhanced market positioning for various participants in the oilseeds business.



With an X-squared value of 28.685 and 5 degrees of freedom, the Box-Ljung test for the residuals of the oilseed production projection reveals a considerable lack of fit. This is indicated by the exceptionally low p-value of 2.674e-05, which is the outcome of the test. Due to the fact that this outcome occurred, it is possible that the existing model does not effectively capture all of the changes and patterns that are present in the data, which results in residuals that are not accounted for. Therefore, it is essential to undertake additional diagnostics and improvements in order to increase the accuracy of the forecasting model and make certain that it appropriately accounts for the underlying patterns and dynamics of the data pertaining to oilseed production. This may be accomplished by ensuring that sufficient time is devoted to the task.

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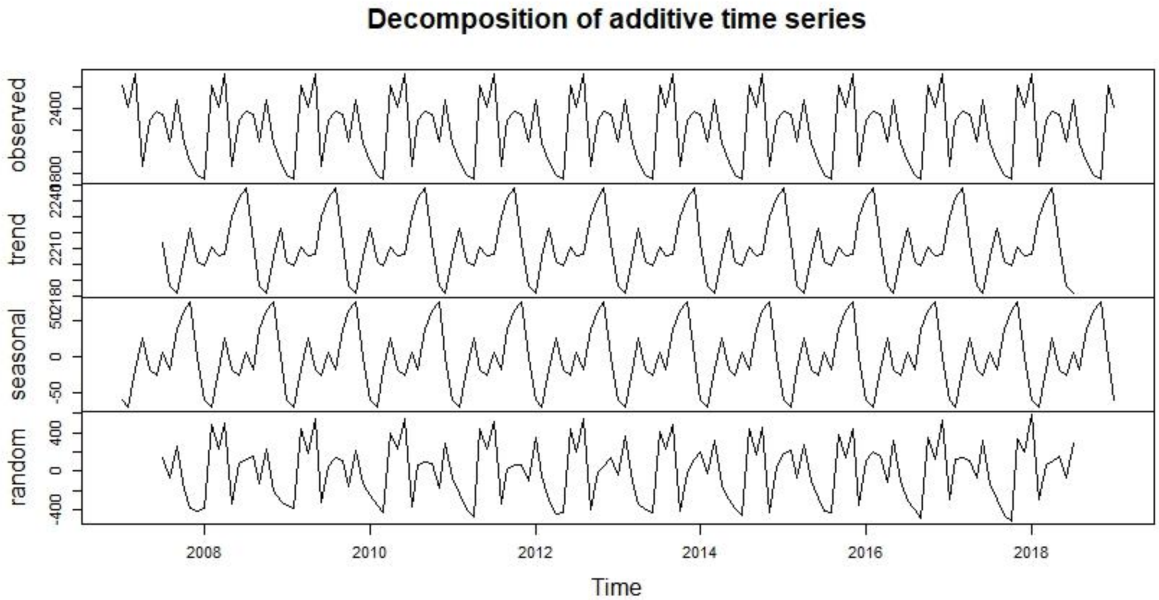

SARIMA

Oilseeds output in the region shows some fascinating trends in the time series data from 2007 to 2019. There have been shifts in the oilseeds crop and harvest across this time period, as shown by the fluctuating production data. There was a high rate of output in the first several years, then it fluctuated. Climate, market conditions, and agricultural techniques are just a few of the variables that have been shown to have an impact on oilseeds output, which has seen both increases and decreases over the years. Understanding these production trends is vital for developing effective strategies for strengthening cultivation methods, assuring steady yields, and mitigating the impact of variable market conditions on the oilseeds sector. These tactics can be used to reduce the impact of these conditions on the oilseeds industry.

The data for oilseeds production in the region were subjected to an enhanced Dickey-Fuller test, which revealed a Dickey-Fuller statistic of -1.8418 and a corresponding p-value of 0.6327. The test did not offer adequate evidence to reject the null hypothesis of non-stationarity because the p-value was much higher than the crucial threshold of 0.05. According to the findings of this statistical examination, the data cannot be thought of as being stationary. It would be necessary to do additional research and analysis in order to achieve a thorough grasp of the underlying patterns and trends included within the oilseeds production statistics.

The essential insights into the dataset were revealed through the compilation of the summary statistics for the time series data on oilseeds production in the region. The lowest value possible was 1748, and the first quartile, median, and third quartile were respectively 1911, 2292, and 2413. The least value possible was 1748. The average production was determined to be 2212 units based on the calculations. During the time period that was being tracked, the highest level of production that was seen was 2730 units. These statistics provide an overview of the central tendency and distribution of the data about oilseeds production, which can then serve as a basis for further research and interpretation.

Differentiated log-transformed time series data on oilseeds production in the area were put through the Augmented Dickey-Fuller (ADF) test. The test yielded a p-value of 0.01, with a Dickey-Fuller statistic of -5.7356. The derived test statistic provides significant evidence against the null hypothesis of non-stationarity and in support of the alternative hypothesis of stationarity. This indicates that there is probably some sort of consistent pattern or trend in the data, as the differenced log-transformed series can be deemed stationary.

Coefficient	Values
σ^2	0.02454
log likelihood	5.22
AIC	-8.44
AICc	-8.04
BIC	-7.95

Oilseeds production time series data was fitted using the auto.arima function. Both the original series and the log-transformed series fit the ARIMA(0,1,0) model as a result. The model's predictions for the original series were a sigma-squared value of 12,4656 and a log-likelihood of -87.43. AIC=176.85, AICc=177.25, and BIC=177.34 were the values obtained from using the information criterion. In contrast, the log-transformed series model has a log-likelihood of 5.22 and a sigma-squared value of 0.02454. AIC=-8.44, AICc=-8.04, and BIC=-7.95 were the values for the information criterion for the log-transformed series. Lower AIC, AICc, and BIC values indicate a better fit, hence they are useful in judging the model's overall quality.

Coefficient	Values
x^2	5.7496
df	1
P-value	0.01649

The ARIMA(0,1,0) model residuals for the log-transformed oilseeds production series were subjected to the Ljung-Box test. The p-value for this test statistic is 0.01649, and the X-squared value is 5.7496 with 1 degrees of freedom. Using this p-value, we may confidently reject the absence of autocorrelation in the

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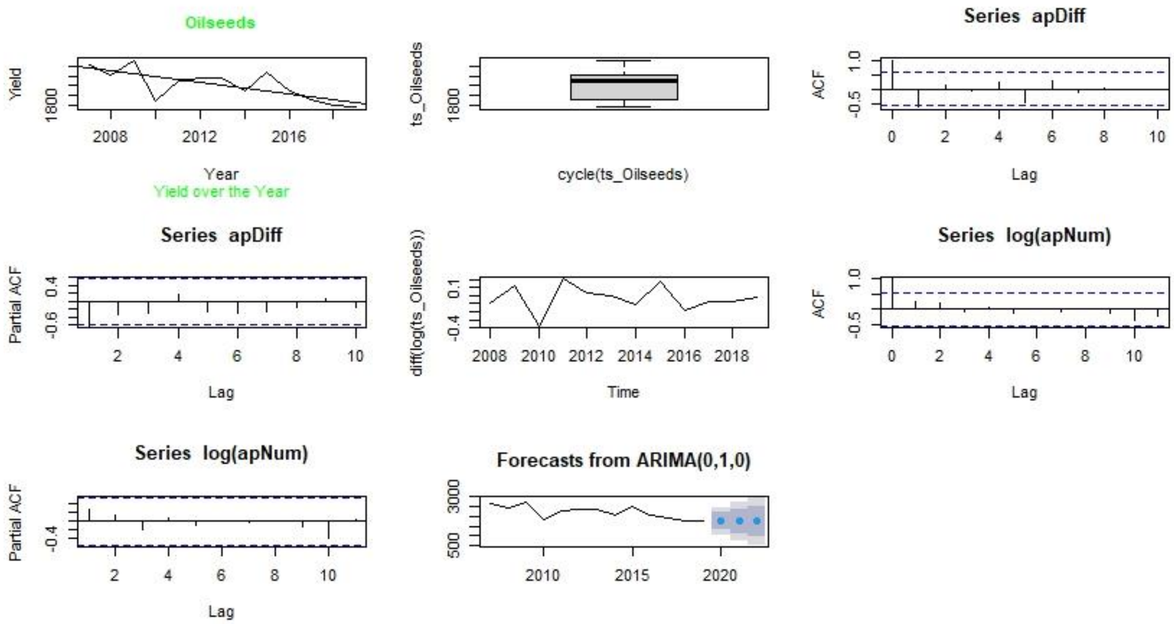
residuals, which is the null hypothesis. Autocorrelation in the residuals is thus supported by the available data.



CONCLUSION:

After doing the studies, one may reach the following conclusion: the ARIMA (0,1,0) model was determined to be suitable for the log-transformed series of time series data pertaining to oilseeds production. This conclusion can be reached on the basis of the findings obtained from the analyses. The Ljung-Box test performed on the ARIMA model's residuals provided evidence that autocorrelation was present in the data. Additionally, the projected values that were produced from this model were consistent, and the Ljung-Box test revealed that the residuals exhibited strong autocorrelation. Because there was no evidence of seasonality in the data, the SARIMA model was not taken into consideration. In addition, the fact that the p-value obtained from the Ljung-Box test conducted on the residuals of the non-seasonal ARIMA model did not show statistical significance suggests that the model is adequate in capturing the underlying patterns present in the oilseeds production time series data.

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