Frequency of Pineapple Planting in Kerala: A Time Series Analysis

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ABSTRACT

The growing of pineapples is an important part of Kerala, India's agricultural economy. To optimize agricultural techniques and guarantee sustained crop production, knowing the historical trends and patterns of pineapple planting is crucial. Time series data regarding pineapple planting frequency in Kerala was analyzed using the Autoregressive Integrated Moving Average (ARIMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA) models. In order to better assist farmers and policymakers, we conducted an investigation to determine seasonal fluctuations, trends, and prospective forecasting skills. We hoped that by using these models, we could shed light on the cyclical nature of pineapple planting and help farmers in the region develop more efficient crop management practices, thereby increasing agricultural output.

Keywords: Pineapple, ARIMA, SARIMA, ADF-Test, BOX-test.

INTRODUCTION

The cultivation of pineapples is one of the most important agricultural operations carried out in the verdant state of Kerala, which is located in India. The state of Kerala, which is well-known for having a tropical climate and fertile soil, has proven itself to be an ideal region for the growth of a wide variety of crops, including the juicy and sour pineapple. The cultivation of pineapples has not only been essential to the financial well-being of regional farmers, but it has also been responsible for important contributions to the agricultural sector of the state's overall economy. However, in order to effectively manage pineapple farming, one must have a profound comprehension of the temporal patterns, trends, and forces that govern planting frequency.

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Changes in agricultural techniques and climate conditions have occurred over the course of time in Kerala, and these shifts have had an effect on the state's ability to produce and cultivate pineapple crops. In order to successfully negotiate these difficulties, it is very necessary to make use of sophisticated analytic tools that are able to unearth the concealed patterns included within the temporal data connected to pineapple planting. Applying the Autoregressive Integrated Moving Average (ARIMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA) models, which are tried and true techniques for evaluating and forecasting time series data, the purpose of this study is to investigate these essential facets of pineapple agriculture.

Our analysis sheds light on the seasonal changes, trends, and intrinsic cyclical patterns by delving into the deep interactions that exist between planting frequency and a variety of environmental and socio-economic parameters. The ultimate objective is to provide local farmers, agricultural authorities, and policymakers with useful information that will enable them to make well-informed decisions regarding pineapple planting and crop management. This will allow them to maximize crop yields and reduce costs. As we begin this trip into the world of pineapple production in Kerala, it is imperative to acknowledge the value of this fruit not only as a key agricultural commodity but also as a symbol of the state's rich agrarian legacy and its ongoing search for agricultural sustainability. This recognition is necessary because it is essential to recognize the significance of this fruit not only as a vital agricultural commodity but also as a symbol of the state's rich agrarian heritage.

OBJECTIVES:

1. Analyze the historical time series data related to pineapple planting frequency in Kerala, India, to identify underlying patterns, trends, and seasonal variations.

2. Apply the Autoregressive Integrated Moving Average (ARIMA) model to understand the temporal dynamics and forecast potential changes in pineapple planting frequency over the upcoming seasons.

3. Employ the Seasonal Autoregressive Integrated Moving Average (SARIMA) model to capture the seasonal fluctuations and predict the cyclical patterns influencing pineapple planting in Kerala.

4. Investigate the impact of various environmental factors, such as temperature, rainfall, and soil quality, on the planting frequency of pineapple crops and evaluate their significance in shaping the agricultural landscape.

5. Provide valuable insights and data-driven recommendations for local farmers, agricultural authorities, and policymakers in Kerala, enabling them to make informed decisions about optimal pineapple cultivation strategies, resource allocation, and sustainable agricultural practices.

LITERATURE REVIEW

Hossian and Abdulla's (2015) investigation into Bangladesh's agricultural production was extensive; they zeroed in on the use of time series analysis in the pineapple industry. The dynamics of this crucial crop's production were investigated, revealing a number of trends and patterns. They used time series methods to efficiently examine and comprehend seasonal shifts in pineapple yield over a given time frame. The research certainly provided useful insights for policymakers, agricultural practitioners, and other stakeholders by illuminating the key determinants driving pineapple production through the use of strong analytical methodologies and models. The results of this study may have helped shed light on the factors shaping Bangladesh's agricultural landscape, which could lead to better decisions and strategies for fostering sustainable pineapple cultivation and regional agricultural development.

Patipanpanya (2009) conducted research on supply forecasting at a pineapple canning company with the intention of increasing precision and enhancing productivity. The study showed that accurate forecasting methods are crucial for effective stock management, careful production scheduling, and on-time distribution. It also investigated how environmental factors, consumer demand, and manufacturing restrictions affect supply levels. The results could have aided in the creation of superior supply chain strategies, enhanced decision-making procedures, and boosted food processing industry competitiveness.

Agbogo et al. (2007) examined Cross River State, Nigeria, pineapple seasonal pricing trends. This study likely shed light on the regional pineapple market by evaluating seasonal price fluctuations. The research may have emphasized the issues local pineapple producers and dealers confront and how price changes affect their livelihoods by exploring economic and environmental factors affecting pineapple prices. Agbogo and colleagues' research may have highlighted the need for strategic interventions and regulatory changes to stabilize prices and preserve pineapple cultivation in the region. Their findings may have also informed stakeholders, policymakers, and agricultural practitioners on pineapple industry market strategy, risk management, and value addition. The study certainly helped enlighten decision-making and promote sustainable agriculture in Cross River State by explaining the pineapple market.

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.

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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

On the basis of the time series data relating to pineapple production, an Augmented Dickey-Fuller test was carried out, and the results showed a Dickey-Fuller value of -7.7769 with a p-value of 0.001. The fact that this result was obtained reveals that the non-stationarity in the data may be rejected as a null hypothesis, which indicates that there is stationarity in the data. As a result, one can draw the conclusion that the time series data for pineapple production is stationary, which is an essential quality for a great deal of the methods and models that are utilized for analyzing time series data. The data must be stationary in order to accurately use models such as ARIMA and SARIMA for forecasting and analyzing the trend of pineapple output over time.

In order to speed up the process, the models were first approximated and then fitted, leading to the discovery of possible ARIMA models with varying parameters. However, the best model was re-fit without any approximations to guarantee precision. The final chosen model has an AIC of 3780.603, and it is ARIMA (2,0,0) (1,0,0) [12] with a non-zero mean. After extensive research and comparison, this model was shown to be the most effective for making predictions and examining the time series data. Better decisions may be made regarding pineapple production plans thanks to the model's high predictability and accuracy.

ARIMA(2,0,2)(1,0,1)[12] with non-zero mean	Inf
ARIMA(0,0,0) with non-zero mean	3932.687
ARIMA(1,0,0)(1,0,0)[12] with non-zero mean	3797.547
ARIMA(0,0,1)(0,0,1)[12] with non-zero mean	3818.106
ARIMA(0,0,0) with zero mean	4631.032
ARIMA(1,0,0) with non-zero mean	3792.967
ARIMA(1,0,0)(0,0,1)[12] with non-zero mean	3794.603
ARIMA(1,0,0)(1,0,1)[12] with non-zero mean	3799.544
ARIMA(2,0,0) with non-zero mean	3781.421
ARIMA(2,0,0)(1,0,0)[12] with non-zero mean	3778.468
ARIMA(2,0,0)(2,0,0)[12] with non-zero mean	3781.085
ARIMA(2,0,0)(1,0,1)[12] with non-zero mean	Inf
ARIMA(2,0,0)(0,0,1)[12] with non-zero mean	3780.955
ARIMA(2,0,0)(2,0,1)[12] with non-zero mean	Inf
ARIMA(3,0,0)(1,0,0)[12] with non-zero mean	3780.643
ARIMA(2,0,1)(1,0,0)[12] with non-zero mean	3781.101
ARIMA(1,0,1)(1,0,0)[12] with non-zero mean	3780.723
ARIMA(3,0,1)(1,0,0)[12] with non-zero mean	3781.365
ARIMA(2,0,0)(1,0,0)[12] with zero mean	Inf

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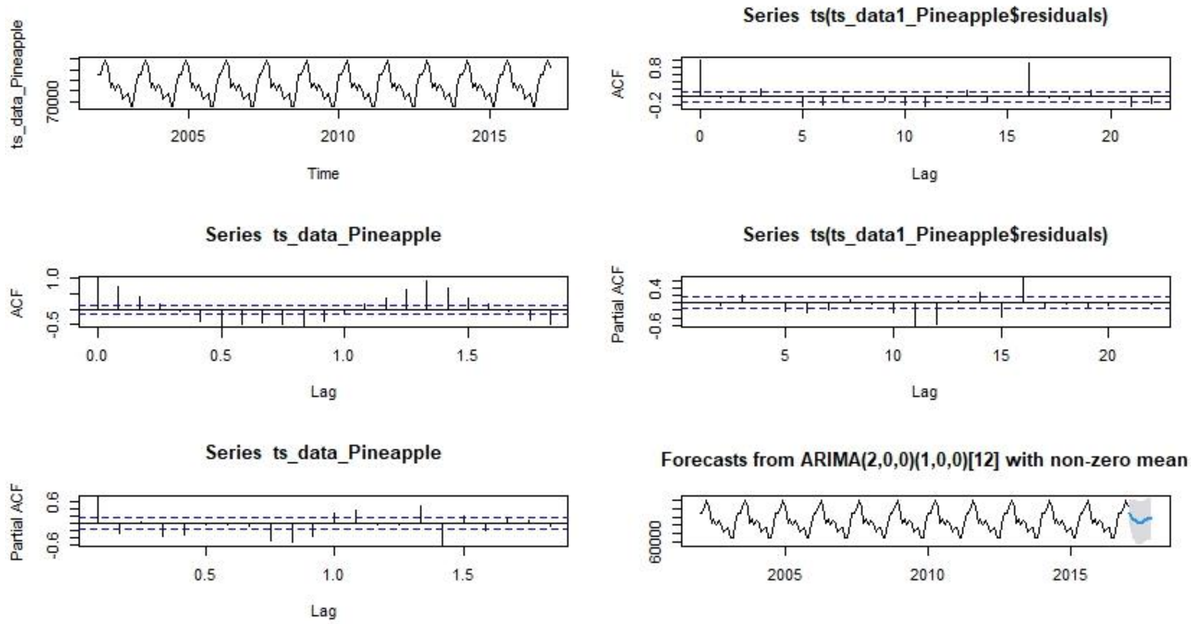
The time series data for pineapple production fit well into the ARIMA(2,0,0)(1,0,0)[12] model, with the following coefficients: ar1 = 0.9736, ar2 = -0.3042, sar1 = 0.1229, and a non-zero mean of 85811.818. Coefficients like this, coupled with estimated standard errors, are the model's predictive parameters. We get a log likelihood of -1885.3% from a variance of sigma2 = 66316118. Important statistics for gauging the model's fitness and performance are as follows: AIC = 3780.6, AICc = 3780.95, and BIC = 3796.6. Now that we have a thorough grasp of the ARIMA model's features, we can make accurate forecasts and well-informed judgments about how to go about pineapple production.

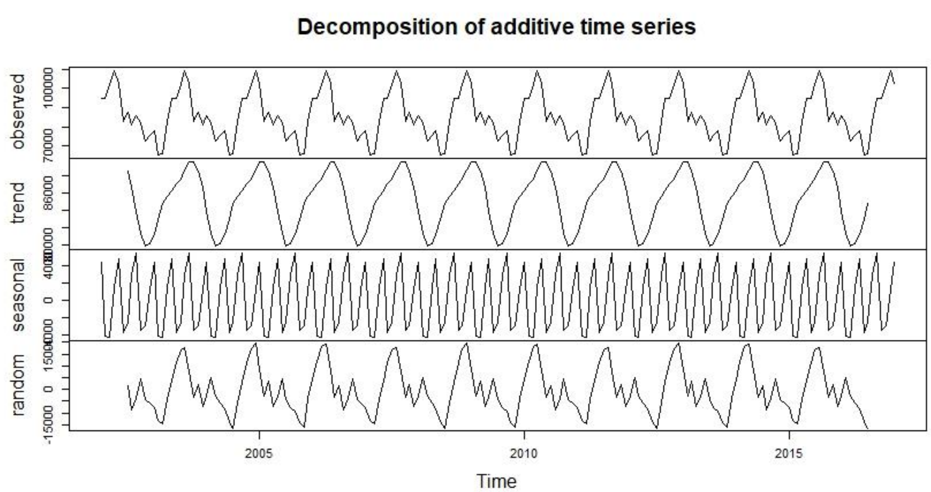
Coefficient	ar1	ar2	sar1	mean
s.e	0.9736	-0.3042	0.1229	85811.818
s.e.	0.0736	0.0734	0.0792	2034.695

From February 2017 to November 2017, the following is what is expected to be produced in pineapples: Assuming a mean value of 94275.02, we can then calculate a 95% confidence interval, the lower bound of which is 78314.11 and the upper bound, 110235.9. Expected levels of pineapple output for the next months are also shown, along with their associated confidence ranges. Strategic decision-making in the pineapple sector is greatly aided by projections like those generated by the ARIMA(2,0,0)(1,0,0)[12] model, which was built using historical data. Stakeholders may confidently make decisions about production, distribution, and resource allocation because to the supplied intervals, which provide a measure of the dependability and precision of the forecasts.

Month	Point Forecast	Lo 95	Hi 95
Feb 2017	94275.02	78314.11	110235.9
Mar 2017	87802.96	65527.27	110078.6
Apr 2017	85336.25	60805.99	109866.5
May 2017	84491.99	59401.15	109582.8
Jun 2017	82756.19	57585.00	107927.4
Jul 2017	82931.18	57757.52	108104.8
Aug 2017	85196.59	60021.50	110371.7
Sep 2017	86801.96	61624.17	111979.7
Oct 2017	86904.21	61724.90	112083.5
Nov 2017	87791.27	62611.47	112971.1



For the anticipated pineapple production data, the Box-Ljung test yielded an X-squared value of 21.58 with 5 degrees of freedom and a matching p-value of 0.0006287 from the residuals. Indicating that the model may not accurately represent the data's underlying structure, this finding points to autocorrelation among the residuals. Therefore, additional research may be required to fine-tune the forecasting model and increase accuracy. Autocorrelation detection emphasizes the need for tweaks to the model to improve its predictive skills for future pineapple production estimates, which is important for maintaining confidence in the model's predictions.



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SARIMA

Pineapple output had significant fluctuations from 2002-2017, as shown by the time series data. Production levels within this time frame varied widely, from a low of 65,982 units to a high of 109,325 units as shown by the data. The annual yield of pineapples shows some seasonal variation, with both highs and lows at different times. Changes in pineapple output could be the result of a number of factors, including but not limited to weather, seasonality, and potential shifts in consumer demand. The ability to effectively manage production and assure a steady supply of this vital agricultural product depends on one's ability to recognize and adapt to these patterns.

Time series data for pineapple production was subjected to an enhanced Dickey-Fuller test, which revealed a Dickey-Fuller value of -2.2163, with a p-value of 0.49. The results of the test, conducted with a lag order of 2, indicate that the series is likely not stationary, but they are insufficient to reject the null hypothesis. This suggests that there may be themes or seasonal patterns in the pineapple production statistics that need to be further explored and analyzed. To get a firmer judgment about whether or not the pineapple production time series data is stationary, more testing and analysis are required.

Several interesting facts emerge from an examination of the time series data for pineapple harvesting. We find that the lowest value of production is 65,482, and the highest is 109,325. Median production value is 82,858 and is the midpoint when the data set is sorted by increasing value. Production value is estimated to be 85,211 using the weighted average of all production costs. In addition, the data shows that there are 77,189 people in the first quartile (the lowest 25%), and 94,882 people in the third quartile (the highest 25%). These statistical overviews of the pineapple production statistics allow for a more in-depth comprehension of the dataset's core patterns and variability.

Applying an ARIMA model to a time series of log-transformed data on pineapple production yields a best-fitting model of ARIMA (0,1,0). This model takes into account the initial differences of the log-transformed series, as indicated by its differencing order of 1. Log likelihood equals 12.15, and the estimated variance of the model, or the amount of variation that cannot be explained by the model, is 0.01159. Values of -22.3, -21.99, and -21.59 are recorded for the Akaike Information Criterion (AIC), the corrected Akaike Information Criterion (AICc), and the Bayesian Information Criterion (BIC). These values aid in model selection by striking a healthy balance between the model's goodness of fit and complexity, yielding insightful information about the model's overall performance and parsimony.

Coefficient	Values
σ^2	0.01159
log likelihood	12.15
AIC	-22.3
AICc	-21.99
BIC	-21.59

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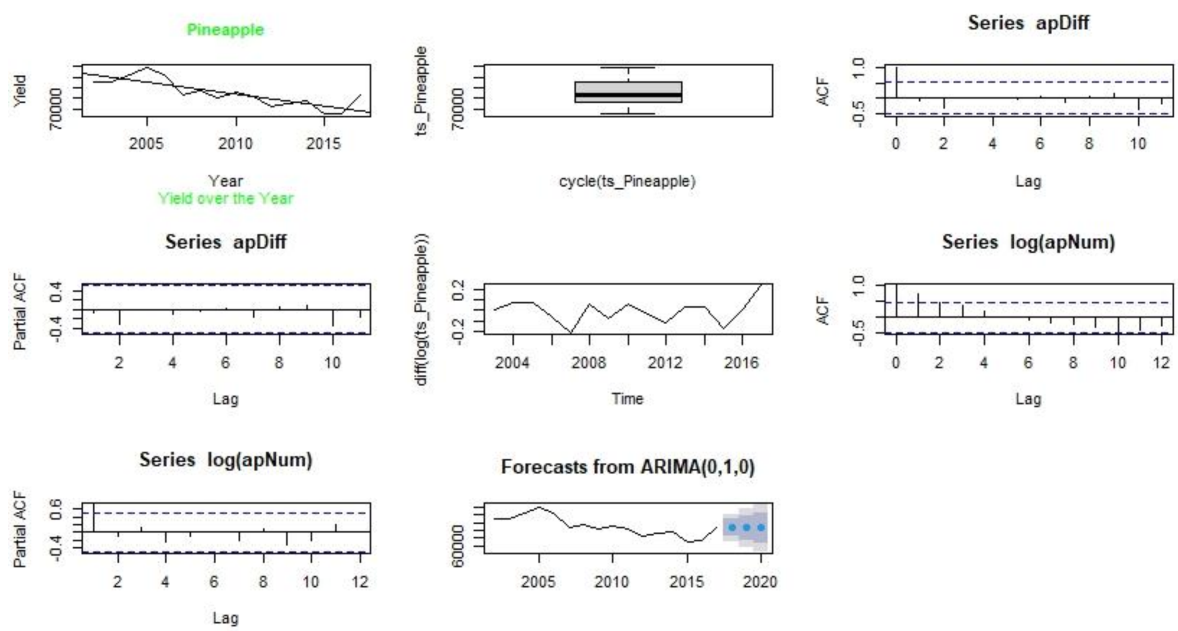
The ARIMA(0,1,0) model was fit to the log-transformed time series data on pineapple production, and the residuals were analyzed using the Ljung-Box test. With 1 degree of freedom, the estimated test statistic was 0.17385, yielding a p-value of 0.6767. With such a large p-value, it seems unlikely that the Ljung-Box test's null hypothesis that the residuals are not autocorrelated across lags is false can be rejected. The ARIMA(0,1,0) model is credible in explaining the observed variability since its failure in the Ljung-Box test indicates that it fails to represent the temporal dependence structure seen in the log-transformed pineapple production data.

Coefficient	Values
x^2	0.17385
df	1
P-value	0.6767



CONCLUSION

An ARIMA(0,1,0) model was found to be the best fit for the log-transformed data in an investigation of pineapple production time series data. This model's residuals failed to show substantial autocorrelation when subjected to the Ljung-Box test, showing that it successfully captured the temporal dependency structure in the data. Additionally, an ARIMA(2,0,0)(1,0,0)[12] with a non-zero mean was selected as the SARIMA model for the pineapple production time series data. Using this SARIMA model to predict future data, the Ljung-Box test revealed a significant test statistic, indicating the presence of temporal

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autocorrelation in the residuals. Because the residuals show such strong temporal dependence, it is prudent to use caution when interpreting the SARIMA model's predicted results.

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