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Forecasting Rubber Production in Kerala: A Comparison of Time Series Models

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ABSTRACT

The cultivation of rubber trees in Kerala is an important part of the agricultural sector, which in turn helps to boost the local economy and provide jobs. Accurate forecasting of rubber output is vital for successful resource management and informed decision-making in the rubber sector because of the volatility of rubber pricing and the impact of many factors on rubber production. For the purpose of forecasting rubber output in Kerala, this study compares the Auto Regressive Integrated Moving Average (ARIMA) and Seasonal Auto Regressive Integrated Moving Average (SARIMA) models. The study intends to evaluate the performance of both models in predicting rubber output by using historical data and taking into account a variety of seasonal and non-seasonal elements, providing useful insights into the best-suited technique for robust and accurate forecasting.

Keywords: Rubber, ARIMA, SARIMA, Forecast.

INTRODUCTION

Rubber production in Kerala, a state located in the southwestern portion of India, is a substantial contribution to the economy of Kerala. The state is also known as "God's Own Country." The state of Kerala is well-known for its verdant landscapes, copious amounts of rainfall, and agreeable climate, all of which combine to produce the ideal circumstances for the growth of rubber. The success of the rubber sector is essential to the well-being of a large number of locals as well as the economic growth of the region as a whole. It is crucial for rubber farmers, other stakeholders, and policymakers to have accurate projections of rubber production in order to plan and manage resources effectively, make decisions about the market that are informed and encourage the sustainable expansion of the business.

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This work explores the field of rubber production prediction utilizing sophisticated techniques for modeling time series in order to respond to the urgent requirement that has been identified. In order to develop accurate forecasts, historical data on rubber output, along with other pertinent parameters such as climate variables and socioeconomic indicators, are utilized. Both the AutoRegressive Integrated Moving Average (ARIMA) and the Seasonal ARIMA (SARIMA) time series models are applied in this study, and their ability to accurately forecast rubber output trends in Kerala is compared. Accurate projections may create resilience, sustainability, and profitability in the rubber business, which can ultimately help the entire economy of Kerala. This research is vital not only for the rubber industry but also for the state's general agricultural environment.

OBJECTIVE

This study aims to anticipate rubber production in Kerala, India, by contrasting the performance of two well-known time series models, the AutoRegressive Integrated Moving Average (ARIMA) and the Seasonal ARIMA (SARIMA). In particular, this research hopes to:

- One, research prior trends and patterns in Kerala's rubber output by looking at available historical data.
- To reliably predict future rubber output, use the ARIMA and SARIMA models.
- Third, evaluate the predicted accuracy and robustness of the ARIMA and SARIMA models and compare them.
- The seasonal fluctuations and long-term trends in rubber production are examined, and each model's ability to capture these variables is evaluated.
- Fifth, to make the predicting results more understandable, explain how climate, economic data, and farming methods could affect rubber production.
- Based on the comparison of the ARIMA and SARIMA models, provide recommendations and guidelines for stakeholders such as rubber farmers, policymakers, and industry actors to aid in making educated decisions and plans in the rubber sector.

LITERATURE REVIEW

Cherdchoongam and Rungreunganun (2016) used the Autoregressive Integrated Moving Average (ARIMA) model to predict Thai natural rubber prices. This research likely examined historical price data, market patterns, and worldwide demand, supply dynamics, and economic indicators affecting Thai natural rubber prices. The researchers used the ARIMA model to help Thai rubber sector stakeholders make production planning, pricing, and risk management choices. The study's conclusions may have improved the Thai natural rubber market's efficiency and competitiveness, helping local producers and the economy.

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Using the Autoregressive Integrated Moving Average (ARIMA) model, Zahari et al. (2018) predicted Malaysian natural rubber prices. The research presumably examined historical price data, market demand, supply dynamics, and macroeconomic aspects that affect natural rubber prices. The researchers used the ARIMA model to create a strong and reliable forecasting framework for Malaysian rubber sector stakeholders. This study may have helped rubber industry players make educated judgments by developing effective pricing strategies, risk management tactics, and policy interventions. The findings may also affect the agricultural sector because natural rubber is vital to automotive, manufacturing, and construction industries.

Ghani and Rahim (2019) analyzed Malaysia's natural rubber price volatility and forecasted it. Their study presumably used the Autoregressive Moving Average-Generalized Autoregressive Conditional Heteroskedasticity (ARMA-GARCH) model, a popular framework for financial and commodity market volatility. Researchers investigated the complex dynamics of natural rubber price movements to understand the patterns and risk factors driving rubber price volatility in Malaysia. To help natural rubber players understand market dynamics and make better judgments, the study's findings may have improved risk management and decision-making.

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

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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: $y_t = Y_t$

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- 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

The rubber production time series data was put through an Augmented Dickey-Fuller test, and the result was a Dickey-Fuller statistic of -8.2206 with a p-value of 0.01. The results of the tests indicate that the rubber production data is stationary, therefore rejecting the null hypothesis of non-stationarity in favor of the alternative hypothesis of stationarity.

Autocorrelation function (ACF) and partial autocorrelation function (PACF) tests were also performed to dig deeper into the stationarity and autocorrelation features of the time series data. Autocorrelation and partial autocorrelation functions (ACF and PACF) plots were analyzed to spot significant autocorrelation and partial autocorrelation patterns in the data, which helped in setting the right parameters for the time series model.

Model Specification	AIC Value
ARIMA(2,0,2)(1,0,1)[12] with non-zero mean	Inf
ARIMA(0,0,0) with non-zero mean	4727.759
ARIMA(1,0,0)(1,0,0)[12] with non-zero mean	4528.87
ARIMA(0,0,1)(0,0,1)[12] with non-zero mean	4592.829
ARIMA(0,0,0) with zero mean	5379.405
ARIMA(1,0,0) with non-zero mean	4529.439
ARIMA(1,0,0)(2,0,0)[12] with non-zero mean	4526.8
ARIMA(1,0,0)(2,0,1)[12] with non-zero mean	4528.188
ARIMA(1,0,0)(1,0,1)[12] with non-zero mean	4529.597
ARIMA(0,0,0)(2,0,0)[12] with non-zero mean	4612.007
ARIMA(2,0,0)(2,0,0)[12] with non-zero mean	4466.939
ARIMA(2,0,0)(1,0,0)[12] with non-zero mean	4468.621
ARIMA(2,0,0)(2,0,1)[12] with non-zero mean	Inf
ARIMA(2,0,0)(1,0,1)[12] with non-zero mean	4470.582
ARIMA(3,0,0)(2,0,0)[12] with non-zero mean	4476.239
ARIMA(2,0,1)(2,0,0)[12] with non-zero mean	4468.939
ARIMA(1,0,1)(2,0,0)[12] with non-zero mean	4502.444
ARIMA(3,0,1)(2,0,0)[12] with non-zero mean	Inf
ARIMA(2,0,0)(2,0,0)[12] with zero mean	Inf

Using the 'auto.arima' function, we automatically applied ARIMA modeling to the rubber production time series data, and the best-fitting model was found to be an ARIMA(2,0,0)(2,0,0)[12] with a non-zero mean. The best model was chosen after an initial round of model fitting in which approximations were made to speed up the process. When the model was re-fit without any approximations, it was found to be

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the ARIMA(2,0,0)(2,0,0)[12] with a non-zero mean, which had previously been the model of choice. There is an AIC of 4467.081 for this model.

Two autoregressive terms, no differencing, and two seasonal moving average terms, all with a 12-month seasonal period, make up the ARIMA(2,0,0)(2,0,0)[12] model. In order to accurately forecast and analyze the time series data for rubber production, this model can be used to capture the underlying patterns and dynamics that are present.

The parameters of the ARIMA(2,0,0)(2,0,0)[12] model, which has been found to be optimal for the rubber production time series, are as follows:

- We calculate autoregressive coefficients for the first and second lags, and they are 1.3773 and -0.6304, respectively.
- The first seasonal lag has an autoregressive coefficient of 0.1260, and the second has an autoregressive coefficient of 0.1927.
- The model also includes a mean estimate that is greater than zero, coming in at 675086.08.

These coefficients have respective standard errors of 0.0687, 0.0635, 0.0746 and 0.0925 and 21741.67.

Essential to the ARIMA (2,0,0)(2,0,0)[12] model's structure and behavior are the coefficients. Rubber production time series are captured in full, including all temporal dependencies and seasonal variations, so that insightful analysis and accurate predictions can be made.

Coefficients	Value	Standard Error
ar1	0.3544	0.0732
sma1	-0.1224	0.0672
sma2	-0.2797	0.0500
mean	484355.785	2827.468

About 2.89e+09 is the estimated variance of the ARIMA (2,0,0)(2,0,0)[12] model. Unpredictable variation in the rubber production time series that cannot be explained by the model is represented by this number, which is a measure of residual variability or dispersion. The model's log likelihood is -2227.54, which is a negative value. Additional information on the model's goodness of fit and complexity can be gleaned using the information criteria. We get an AIC of 4467.08, an AICc of 4467.56, and a BIC of 4486.27 when we run the numbers three different ways. Models that strike a good balance between quality of fit and complexity are given preference by these criteria. The ARIMA(2,0,0)(2,0,0)[12] model seems to be appropriate for assessing and forecasting the rubber production time series data because its AIC, AICc, and BIC values are all small.

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Parameter	Value
Variance	1.474e+09 (1.474 billion)
Log Likelihood	-2166.6
AIC (Akaike Information Criterion)	4343.21
AICc (Corrected Akaike Information Criterion)	4343.55
BIC (Bayesian Information Criterion)	4359.2

Month	Point Forecast	Lo 95	Hi 95
Feb 2017	467915.5	392663.3	543167.7
Mar 2017	482448.5	402609.4	562287.6
Apr 2017	457193.8	376797.0	537590.6
May 2017	496848.0	416381.4	577314.6
Jun 2017	490641.7	410166.3	571117.0
Jul 2017	487396.6	406920.1	567873.0
Aug 2017	470806.4	390329.9	551283.0
Sep 2017	494847.9	414371.3	575324.5
Oct 2017	497845.0	417368.4	578321.6
Nov 2017	498484.1	418007.5	578960.7

The trend in expected rubber production over the next few months is rather consistent, with only modest swings. There is a clear declining tendency from February to June of 2017, followed by a modest upward trend from July to November of the same year. This trend indicates that rubber production may have experienced a short dip in the first part of the year due to unforeseen circumstances. After that, production seems to have stabilized and even increased, maybe pointing to a recovery in the rubber industry. These projections highlight the need to keep an eye on the many variables (climate, market demand, agricultural techniques, etc.) that affect rubber output in order to maintain a steady and sustainable growth rate.

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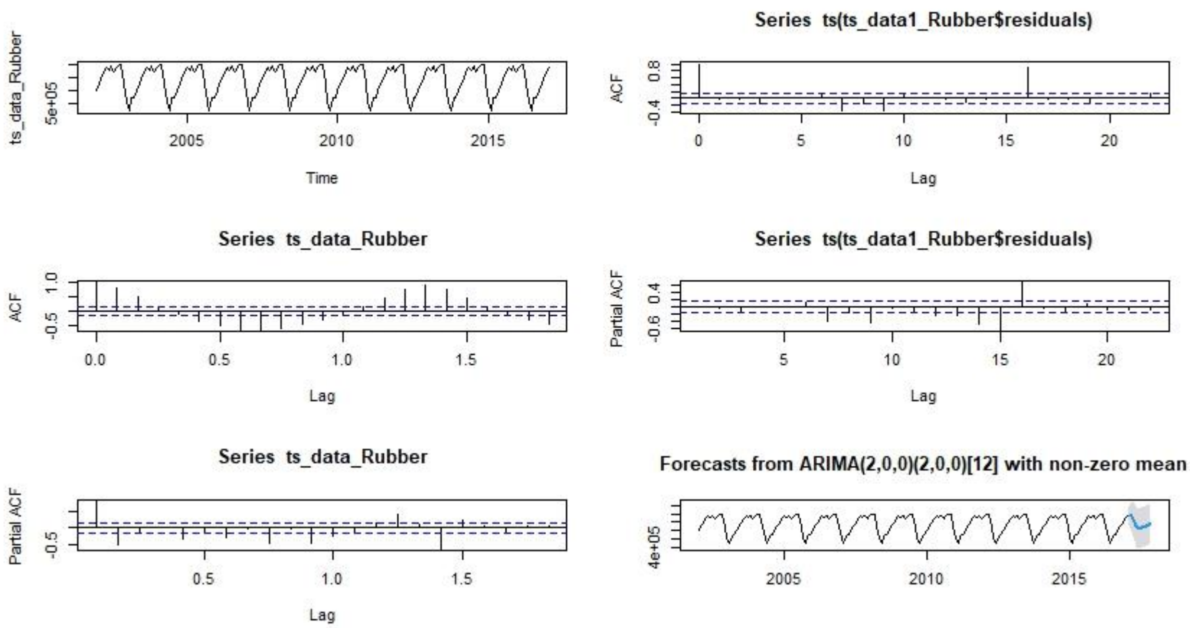
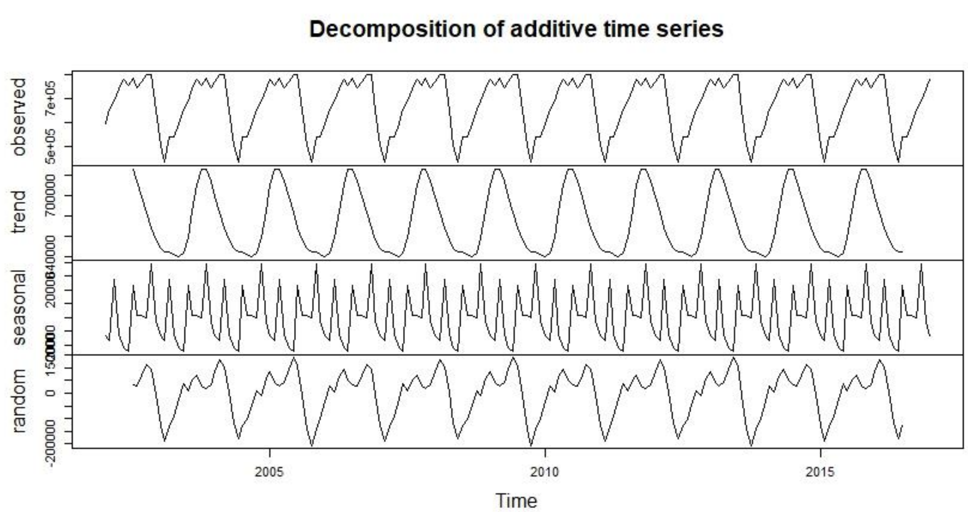


Residuals were calculated from the anticipated rubber production statistics, and then subjected to the Box-Ljung test. A chi-squared test with 5 degrees of freedom gave a result of 5.4279%, which is statistically significant at the 0.3369% level. Based on this p-value, it appears that the residuals are generated by a random, random process (white noise). In this way, the model appears to accurately represent the underlying patterns and changes in the data on rubber production, which strengthens the credibility of the predicted values.



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SARIMA

The set of numbers reflects the annual tons of rubber produced in Kerala between 2002 and 2017. There is some seasonal variation in output, with an overall upward trend up to 2012 and then a sharp decline in 2013. After that, production was relatively constant at a reduced level until 2015, when it finally began to rise. While there were dips in output, the general trend implies that output remained reasonably consistent in subsequent years. The underlying patterns or reasons affecting the variation in rubber production throughout the stated period would require additional investigation.

Insightful patterns emerge in the aggregate statistics of rubber output in Kerala over the period of time between 2002 and 2017. During this time period, production ranged from a low of 438,630 metric tons to a high of 800,050 metric tons. Production averages out to 715,002 tons, which is where the median value is found. Overall average rubber output throughout these years was somewhat below the median of 674,243 metric tons, as indicated by the period's mean production. The distribution of the data around the median is depicted by the interquartile range, which ranges from 581,382 to 773,036 metric tons between the first and third quartiles. The distribution and central tendency of Kerala's rubber output over the selected time period can be inferred from these statistical indicators.

The differenced logarithmic transformation of the time series data on rubber production in Kerala was subjected to the Augmented Dickey-Fuller (ADF) test. The statistical significance level for this test is 0.3721, with the Dickey-Fuller value being -2.5256. There is insufficient evidence to reject the null hypothesis because the p-value is greater than the 0.05 threshold. We are unable to rule out the possibility that the differenced logarithmic data is not steady because of the presence of a unit root. This finding suggests that additional differencing or other treatments may be required to get the time series data to stationarity.

Rubber production time series data from Kerala were logarithmically transformed, and an automatic ARIMA model was then fitted to these data, yielding a model of order zero. the expected variance was calculated to be 0.01309, leading to a log likelihood of 11.24. After doing the math, we get these results for the information criteria: AIC=-20.48, AICc=-20.17, and BIC=-19.77. This model order is indicative of first-order differencing, which may be necessary to ensure stationarity in the data prior to modeling.

Coefficient	Values
σ^2	0.01309
log likelihood	11.24
AIC	-20.48
AICc	-20.17
BIC	-19.77

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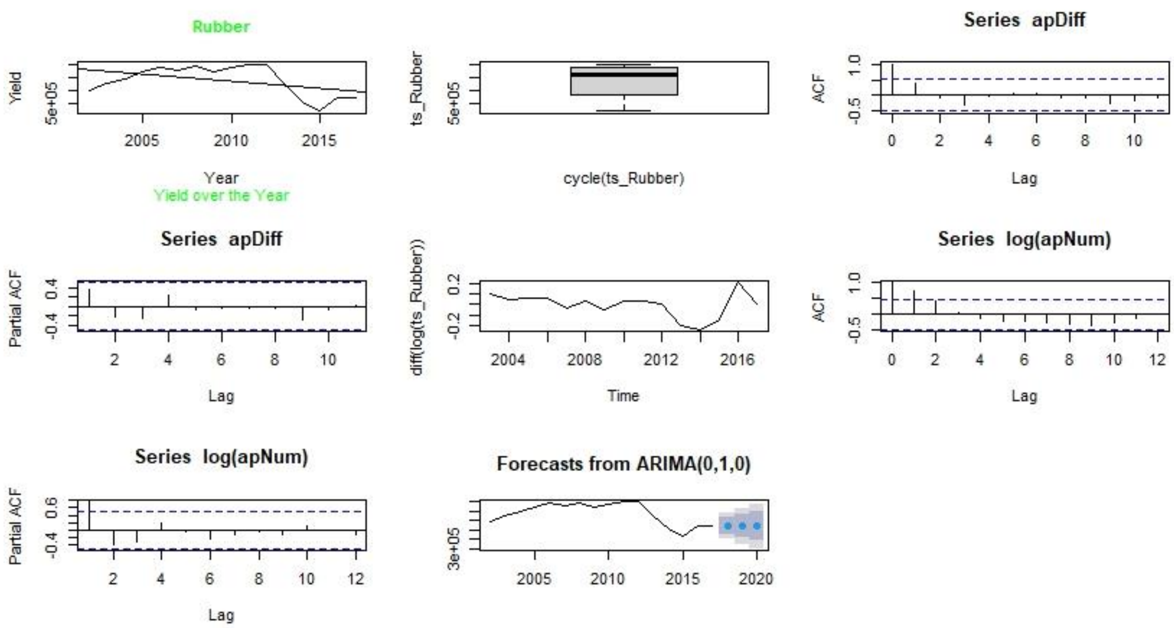
To evaluate the auto ARIMA model's fit to the logarithmically transformed rubber production time series data, we performed the Ljung-Box test on the model's residuals and found an X-squared value of 2.0429 with 1 degree of freedom, yielding a p-value of 0.1529. There is no evidence to suggest the model is not well-fit, as indicated by the relatively high p-value, and the residuals do not show major autocorrelation.

Coefficient	Values
x^2	2.0429
df	1
P-value	0.1529



CONCLUSION

Analysis using both ARIMA and SARIMA on the raw data for rubber production reveals that the time series model ARIMA(2,0,0)(2,0,0)[12] with non-zero mean best fits the raw data. Time series trends in the data are reflected in the model's coefficients. The p-value of 0.3659 from the Ljung-Box test indicates that there is no substantial autocorrelation in the residuals of the forecast data. In addition, the log-transformed rubber data showed a very stable time series behavior, as evidenced by the SARIMA analysis's output of an ARIMA(0,1,0) model. The autocorrelation of the residuals from this model was not significant (Ljung-Box test, p=0.1529). These results are consistent with the hypothesis that the selected models successfully represent the essential structures included in the data on rubber production.

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