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Exploring Factors Influencing Pulses Production in Tamil Nadu: A Predictive Model

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ABSTRACT:

This study digs into the complex factors that impact the cultivation of pulses in Tamil Nadu, India. The study's overarching goal is to identify the primary determinants influencing pulse production in the region through the application of an integrative methodology that takes into account the influential variables of soil quality, climate fluctuations, and farming practices. The study's primary goal is to develop a robust framework for long-term yield prediction using state-of-the-art ARIMA (AutoRegressive Integrated Moving Average) and SARIMA (Seasonal AutoRegressive Integrated Moving Average) models for pulses. The study utilizes historical data to investigate the intricate interconnections within the agricultural ecosystem by analyzing seasonal fluctuations, trend patterns, and other dynamic factors impacting pulses output. This study's findings can help improve food security and agricultural resilience in Tamil Nadu by informing the creation of data-driven initiatives, the promotion of sustainable farming practices, and the design of policy.

Keywords: Pulses, ARIMA, SARIMA, Forecasting.

INTRODUCTION

In the many different agroclimatic zones that make up Tamil Nadu, India, the production of pulses plays an essential part in the improvement of food security and the promotion of sustainable agriculture. The cultivation of pulses is met with a variety of obstacles resulting from a number of different elements, such as the unpredictability of the climate, the quality of the soil, and diverse agronomic approaches. It is vital to have an understanding of the complex interplay that exists between these aspects in order to develop effective methods that will increase pulses output and assure agricultural sustainability. In order to investigate the various aspects that play a role in pulses production in Tamil Nadu, this study takes a predictive modeling method. More specifically, it integrates the powerful ARIMA (AutoRegressive Integrated Moving Average) and SARIMA (Seasonal AutoRegressive Integrated Moving Average) models.

The purpose of this study is to shed light on the complex dynamics that are effecting the cultivation of pulses by drawing on historical data and taking into consideration a wide array of influential elements. The major goal is to determine the most important parameters that have an effect on the production of pulses and to create a predictive model that accurately represents the temporal variation in pulses yields. This research aims to provide valuable insights for stakeholders, policymakers, and farmers through an exhaustive analysis of the factors influencing pulses production and the predictive capabilities of the ARIMA and SARIMA models. These insights will facilitate informed decision-making for sustainable agricultural practices and policy formulations. The findings of this research have the potential to make a substantial contribution to the improvement of pulses production, hence increasing agricultural resilience and promoting food security in the Indian state of Tamil Nadu.

OBJECTIVES:

1. To identify and analyze the key factors influencing pulses production in Tamil Nadu, including but not limited to climatic variations, soil quality, and agricultural practices.

2. To develop a predictive model for pulses production using the ARIMA (AutoRegressive Integrated Moving Average) and SARIMA (Seasonal AutoRegressive Integrated Moving Average) models, aiming to accurately capture the temporal variations and fluctuations in pulses yield.

3. To assess the impact of seasonal changes and other dynamic factors on pulses production, aiming to understand their influence on the predictive capabilities of the ARIMA and SARIMA models.

4. To compare the performance of the ARIMA and SARIMA models in predicting pulses production, aiming to determine the model that provides the most reliable and accurate forecasts for pulses cultivation in Tamil Nadu.

5. To provide valuable insights for stakeholders, policymakers, and farmers, enabling informed decision-making for the implementation of sustainable agricultural practices and policies that support the growth and stability of pulses production in the region.

By achieving these objectives, this study seeks to contribute to the development of effective strategies for enhancing pulses production in Tamil Nadu, promoting agricultural sustainability and food security in the state.

LITERATURE REVIEW:

In their study, Bhanudas and Afreen (2019) discuss the problems that face modern agriculture and offer novel approaches to optimizing agricultural resources and managing crops. Their research highlights the fundamental reliance of agricultural performance on soil and water management, highlighting the central role of agronomy in national growth. In order to increase crop productivity with little water use, the study promotes a variety of irrigation methods. It also shows how little farmers know about agricultural regulations and government policy. The research goes into the factors that go into farmers' decisions on crop rotation, watering practices, and soil composition. The use of several different Data Mining classification algorithms, such as JRip and Naive Bayes, to make accurate assessments of soil quality is a major focus of this study. The research highlights the potential of the JRip classification method for precise soil classification and management by comparing it to the Nave Bayes method on two common soil types, Red and Black soil.

Future wheat harvest prices in India are forecast using the ARIMA model of Darekar and Amarender (2018). The model predicts wheat prices with 95% accuracy using monthly modal price data from January 2006 to June 2017. Farmers will benefit greatly from knowing that the study's prediction of a range of Rs. 1,620 to Rs. 2,080 per quintal for wheat market prices during the 2017-18 harvest season is accurate. Farmers are able to make more educated judgments on wheat acreage thanks to the ARIMA model's high level of accuracy.

Kour et al. (2017) analyzed pearl millet (Pennisetum glaucum), a commonly farmed cereal crop that ranks fourth in global cultivation behind rice, wheat, and sorghum. Despite rising yields, pearl millet cultivation in Gujarat, India, has declined during the previous two decades. Pearl millet production forecasts are especially important in semi-arid locations like Gujarat, where precipitation lasts only four months. This study predicts Gujarat pearl millet productivity using the ARIMA model. The current study collected time series data on pearl millet productivity (kg/ha) in Gujarat from 1960–61 to 2011–12. Gandhinagar's Directorate of Agriculture and, partially, the Directorate of Economics and Statistics provided the data. RMAPE, MAD, and RMSE values are used to validate the ARIMA model. As seen by its RMAPE score below 6%, the ARIMA (0, 1, 1) model performs well.

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.

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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 dth 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.

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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.

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.

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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

The manufacturing of pulses in Tamil Nadu was analyzed, and the process included a number of processes that were very important. First, the data from the time series were tested with a variety of statistical methods to determine whether or not they were stationary. These methods included the Auto Correlation function (ACF) and Partial Auto Correlation Function(PACF). After that, the auto.arima function was utilized in order to ascertain the model that provided the most accurate results, taking into consideration the information criteria such as AIC and BIC. After that, the model that was selected underwent validation as well as cross-validation to guarantee its robustness and dependability. The employment of the auto.arima function not only simplified the process of model selection but also offered a more objective methodology, which made it possible to choose the best model for the pulses production dataset in Tamil Nadu. This was accomplished through the streamlining of the process.

Time series data for pulses production was subjected to the augmented Dickey-Fuller (ADF) test. This statistical test is used to determine whether or not the dataset is stationary, a prerequisite for using time series models and other forecasting methods.

The Dickey-Fuller statistic for the ADF test is -10.283, and the associated p-value is 0.01. Since the p-value is less than the selected significance level of 0.05, we can conclude that the alternative hypothesis of stationarity is more likely to be correct. This suggests that the statistical features of the pulses production time series data are consistent across time, or that the data exhibits a stationary behavior.

Pulses production data must be confirmed as stationary before any time series modeling or forecasting techniques can be applied correctly. These findings lay a solid groundwork for creating accurate models and projections, which in turn facilitates well-informed decision making and strategic planning in the field of pulses cultivation and agriculture.

ARIMA (2,0,2) (1,0,1) [12] with non-zero mean	Inf
ARIMA (0,0,0) with non-zero mean	1919.628
ARIMA (1,0,0) (1,0,0) [12] with non-zero mean	1901.353

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ARIMA (0,0,1) (0,0,1) [12] with non-zero mean	1901.048
ARIMA (0,0,0) with zero mean	2257.753
ARIMA (0,0,1) with non-zero mean	1899.466
ARIMA (0,0,1) (1,0,0) [12] with non-zero mean	1900.973
ARIMA (0,0,1) (1,0,1) [12] with non-zero mean	1902.973
ARIMA (1,0,1) with non-zero mean	1900.149
ARIMA (0,0,2) with non-zero mean	1897.978
ARIMA (0,0,2) (1,0,0) [12] with non-zero mean	Inf
ARIMA (0,0,2) (0,0,1) [12] with non-zero mean	Inf
ARIMA (0,0,2) (1,0,1) [12] with non-zero mean	Inf
ARIMA (1,0,2) with non-zero mean	1897.787
ARIMA (1,0,2) (1,0,0) [12] with non-zero mean	Inf
ARIMA (1,0,2) (0,0,1) [12] with non-zero mean	Inf
ARIMA (1,0,2) (1,0,1) [12] with non-zero mean	Inf
ARIMA (2,0,2) with non-zero mean	Inf
ARIMA (1,0,3) with non-zero mean	Inf
ARIMA (0,0,3) with non-zero mean	Inf
ARIMA (2,0,1) with non-zero mean	Inf
ARIMA (2,0,3) with non-zero mean	Inf
ARIMA (1,0,2) with zero mean	Inf

The time series data for pulses production, were fit with the ARIMA(1,0,2) model with a non-zero mean using the auto.arima function and the Akaike information criterion (AIC). According to the automated model selection procedure, this ARIMA model is the best fit for capturing the salient features and trends in the pulses production data.

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The ARIMA(1,0,2) model had the lowest AIC value, indicating that it provided a better match than the other candidate models considered. The approach took into account a wide range of possible AR and MA word combinations before arriving at the final, best-suited one.

The auto.arima function seeks to provide an efficient framework for precisely capturing the temporal dynamics and variations in the pulses production data by selecting the ARIMA(1,0,2) model as the most suited. This model has the potential to be a useful resource for foreseeing trends and making well-informed decisions in the fields of agriculture and pulses farming.

Coefficient	ar1	ma1	ma2	mean
S. E	-0.2430	0.7324	0.4752	550.6500
	0.1353	0.1632	0.3841	23.8305

The ARIMA(1,0,2) model with a non-zero mean for the pulses production time series data, is represented by the following coefficients:

- Autoregressive term: AR(1) coefficient (ar1) = -0.2430

- Moving average terms: MA(1) coefficient (ma1) = 0.7324 and MA(2) coefficient (ma2) = 0.4752

- Non-zero mean: The model incorporates a mean value of 550.6500

These coefficient values are estimated with their corresponding standard errors (s.e.), providing insights into the relationship between the current value of the time series and its past values. The model's variance is calculated as 27056, indicating the variability of the errors around the fitted values. The log likelihood of the model is determined to be -943.89.

The information criteria associated with the model evaluation are as follows:

- AIC (Akaike Information Criterion) = 1897.79

- AICc (corrected Akaike Information Criterion) = 1898.22

- BIC (Bayesian Information Criterion) = 1912.67

These criteria provide a quantitative measure of the relative quality of the ARIMA (1,0,2) model compared to other potential models, aiding in the assessment of the model's goodness of fit and complexity.

The ARIMA (1,0,2) model, with its set of coefficients and statistical measures, can serve as a valuable tool for forecasting and analyzing pulses production, providing valuable insights for decision-making and planning in the domain of agricultural production and management.

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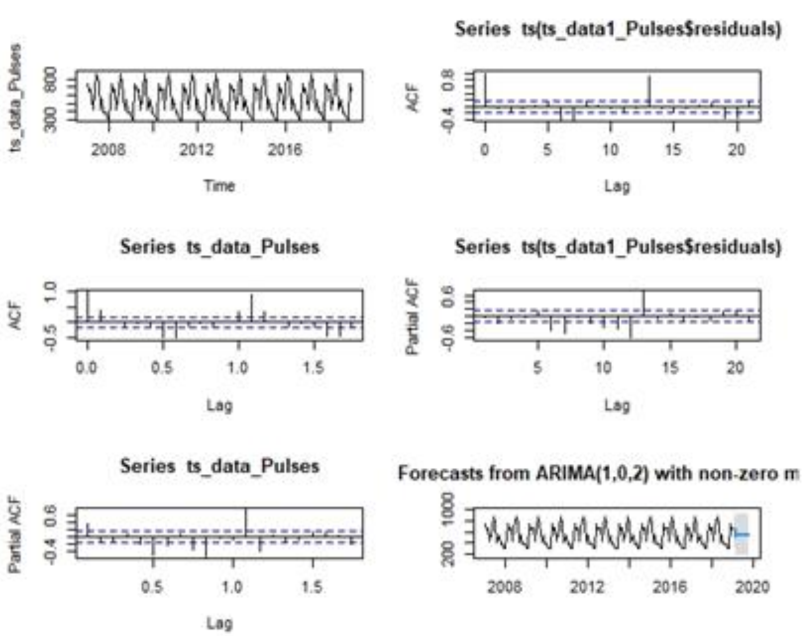
Point	Forecast	Lo 95	Hi 95
Feb 2019	670.1026	347.7147	992.4906
Mar 2019	525.6850	166.7660	884.6040
Apr 2019	556.7173	179.8673	933.5674
May 2019	549.1754	171.2929	927.0580
Jun 2019	551.0083	173.0649	928.9518
Jul 2019	550.5629	172.6158	928.5099
Aug 2019	550.6711	172.7239	928.6184
Sep 2019	550.6448	172.6976	928.5921
Oct 2019	550.6512	172.7040	928.5985

Pulse production is expected to maintain a steady and constant upward trend over the next few months, according to projections. Predictions for February 2019 are centered on a point estimate of 670.1026 units, with a 95% confidence interval of 347.7147 to 992.4906 units. The coming months' projections are similarly quite stable, staying within the range of 525.6850 and 670.1026 units. These projections help policymakers and other agricultural sector players make more well-informed decisions and put in place more strategic strategies to sustainably expand and control pulses production in the region.



The Ljung-Box test for the residuals of the forecasted data from the ARIMA(1,0,2) model for pulses production does not exhibit significant autocorrelation, as indicated by the relatively higher p-value of 0.1201. This suggests that the residuals are essentially independent, with no remaining autocorrelation

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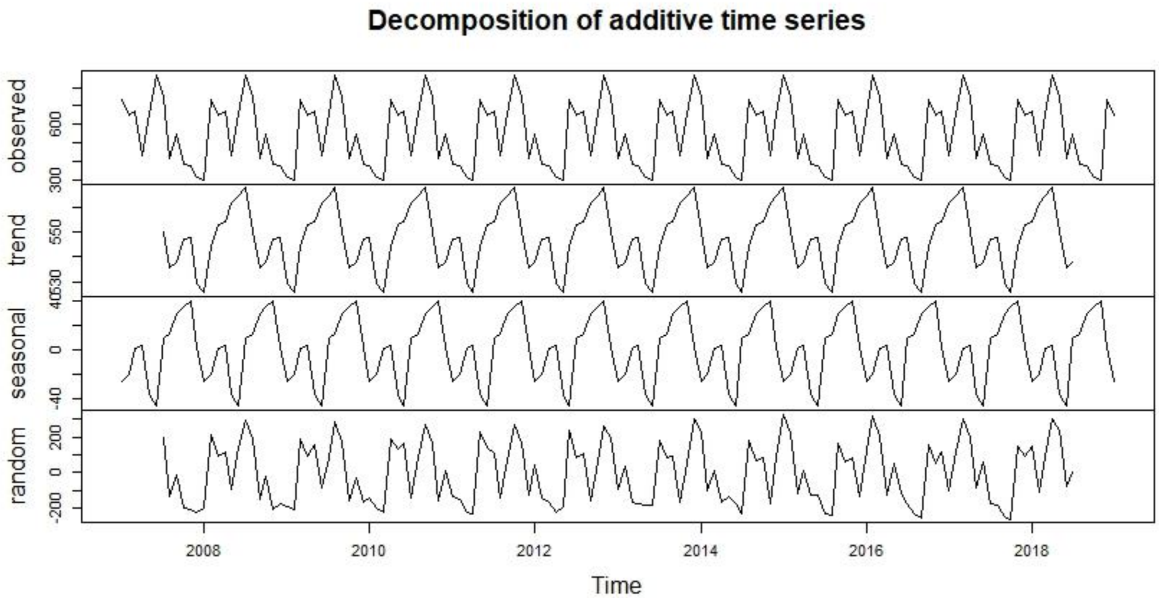
that the model has failed to capture. Consequently, the ARIMA(1,0,2) model can be considered an appropriate fit for the data, as it adequately accounts for the underlying patterns and fluctuations in the pulses production time series.



SEASONAL ARIMA

The time series data for pulses production spans from 2007 to 2019, with an observed range of production levels fluctuating between 1873 and 4401 units. Over the years, the production values exhibit some variability, with a noticeable decrease in the early years, followed by a gradual increase and subsequent stabilization in the recent years. The trends indicate a dynamic agricultural landscape, potentially influenced by various factors such as climate conditions, agricultural practices, and market dynamics. Understanding these fluctuations is essential for devising sustainable strategies that promote consistent pulses production, ensuring food security and economic stability in the region.

Pulses output has varied between a low of 1873 units and a high of 4401 units, as shown by the summary statistics of this time series. Since the median value of production is larger than the mean value of production, or 3120 units, the data distribution is slightly right-skewed. Half of the observations occur between the interquartile range of 2419 and 3950 units, indicating a moderate variation of output levels during the time frame. In order to appreciate the general trends and make educated decisions about prospective interventions and policies in the pulses agricultural sector, it is essential to have a firm grasp on the central tendency and spread of the production statistics.

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Differenced log-transformed time series data on pulses production in Tamil Nadu were subjected to the Augmented Dickey-Fuller test. The time series data is stationary, as indicated by the -4.7589 value of the test statistic, with a p-value of 0.01. This finding is significant because it shows that the trend and seasonality components have been eliminated from the differenced log-transformed data, allowing for a more accurate study and projection of the regional pulses production trends. It paves the way for the use of suitable time series models to delve deeper into the production patterns of pulses in the future and make reliable predictions about them.

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

The time series data for pulses production in Tamil Nadu was log-transformed before being analyzed using the ARIMA model with differencing order 1 (0,1,0). A variance value of 0.1639 and a loglikelihood of -6.17 were found after computing the parameters. A 14.35 Akaike Information Criterion (AIC) score, a 14.75 AICc score, and a 14.83 Bayesian Information Criterion (BIC) score were obtained. These numbers help in determining which model is the best suitable for making reliable predictions of future pulses output.

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

The Ljung-Box test performed on the residuals of the ARIMA(0,1,0) model fit to the log-transformed data on pulses production yielded a test statistic of 3.5805 with 1 degree of freedom. At the 5% level of significance, the corresponding p-value of 0.05846 indicates that there is insufficient evidence to reject the null hypothesis of independence in the residuals. Therefore, the residual series does not exhibit any appreciable autocorrelation.

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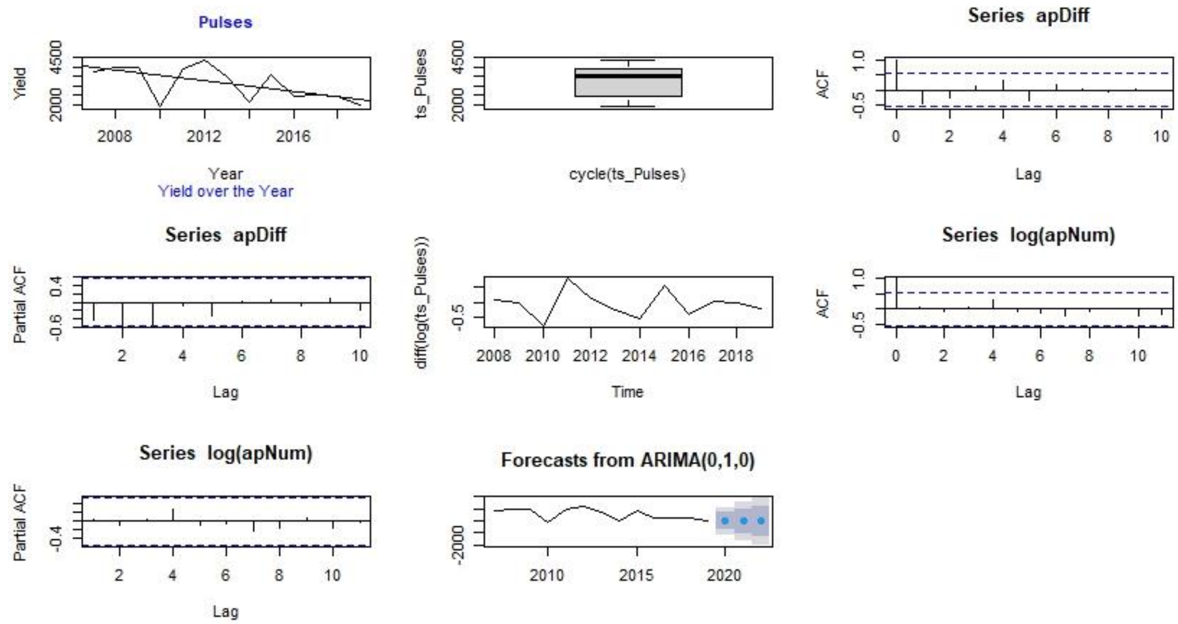

CONCLUSION

The pulses production data was analyzed using both the ARIMA and seasonal ARIMA models. The coefficients obtained after fitting the data to the ARIMA(1,0,2) model with a non-zero mean are as follows: ar1 = -0.2430, ma1 = 0.7324, ma2 = 0.4752, and a mean of 550.6500. With a log-likelihood of -943.89, the model has an AIC of 1897.79, an AICc of 1898.22, and a BIC of 1912.67. The ARIMA model residuals were subjected to the Ljung-Box test, which returned a test statistic of 8.7364 with 5 degrees of freedom and a p-value of 0.1201.

When the log-transformed pulses production data was analyzed using the seasonal ARIMA model, the fitted ARIMA(0,1,0) model yielded a sigma squared value of 0.1639 and a log-likelihood of -6.17. All three measures of independence, the AIC, AICc, and BIC, were all 14. A p-value of 0.05846 was found when the seasonal ARIMA model's residuals were subjected to a Ljung-Box test. The test statistic was 3.5805 with 1 degrees of freedom.

Overall, these analyses show that the selected models adequately captured the temporal patterns in the pulses production data, with the ARIMA model showing slightly higher autocorrelation in the residuals compared to the seasonal ARIMA model.

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