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A Comparative Study of Time Series Models for Millets Yield Prediction in Tamil Nadu

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ABSTRACT

The purpose of this research was to evaluate and contrast time series models for predicting millet yield in the context of agricultural output in Tamil Nadu, India. The study's overarching goal is to shed light on the prediction capacities of ARIMA (AutoRegressive Integrated Moving Average) and SARIMA (Seasonal AutoRegressive Integrated Moving Average) models as they pertain to millet farming by examining their respective applications. The purpose of this research is to determine the efficacy of the ARIMA and SARIMA models in capturing the nuances of millet yield fluctuations by using historical data covering various influential factors like climatic variations, soil conditions, and agricultural practices. To further develop prediction approaches for sustainable agricultural planning and decision-making, this comparison sheds light on seasonal trends, trend changes, and other dynamic components driving millet output. In order to maximize millet output and guarantee food security in the Tamil Nadu area, this study is crucial in promoting the implementation of data-driven solutions.

Keywords: Millets, ARIMA, SARIMA, Forecasting.

INTRODUCTION

Millets, a key part of Tamil Nadu's agricultural landscape, have risen to prominence in recent years as a result of their resistance to the effects of unfavorable weather conditions and the nutritional value they provide for maintaining food security. There is an increasing demand for the development of reliable predictive models that are capable of accurately predicting millet yields. This demand is being driven by the growing significance of millet farming in the context of sustainable agriculture. In this study, a complete comparative analysis of time series models to forecast millet yields in Tamil Nadu is carried out. A particular emphasis is placed on the AutoRegressive Integrated Moving Average (ARIMA) model and the Seasonal AutoRegressive Integrated Moving Average (SARIMA) model. This research aims to identify the strengths and limitations of the ARIMA and SARIMA models in accurately capturing the complex dynamics of millet yield fluctuations. This will be accomplished by utilizing historical data and taking into consideration a wide range of influential factors such as variations in the climate, the quality of the soil, and various agricultural practices.

The fundamental objective of this investigation is to develop a comprehensive understanding of the seasonal patterns, trend changes, and other dynamic components that significantly influence millet output. This research seeks to provide useful insights into the temporal variability of millet yields by comparing the predictive capacities of the ARIMA and SARIMA models. These insights will enable stakeholders to make educated decisions about agricultural planning and policy formation. Not only does the incorporation of sophisticated time series analytic techniques contribute to the refining of predictive approaches for millet cultivation, but it also aids the development of sustainable agricultural practices that are adapted to the specific demands of Tamil Nadu's agro-ecological landscape. This is because of the fact that these techniques are able to better account for the interplay between environmental and agronomic factors. This comparative study has a significant amount of promise for building agricultural resilience and boosting food security, thereby ensuring the continued growth of the agricultural sector in Tamil Nadu, which is essential for the state's economy.

OBJECTIVES:

1. To examine the historical time series data of millet yield in Tamil Nadu and identify the seasonal and trend patterns that influence yield fluctuations.

2. To apply the ARIMA (AutoRegressive Integrated Moving Average) and SARIMA (Seasonal AutoRegressive Integrated Moving Average) models for millet yield prediction and assess their effectiveness in capturing the intricate dynamics of millet production.

3. To evaluate the performance of the ARIMA and SARIMA models in terms of their ability to account for seasonal variations and long-term trends in millet yield, aiming to determine the model that provides the most accurate and reliable predictions for millet production in the region.

4. To investigate the key factors influencing millet production, including climatic variability, soil quality, and agricultural practices, and to ascertain their impact on the predictive capabilities of the ARIMA and SARIMA models.

5. To provide valuable insights for farmers, policymakers, and stakeholders, facilitating informed decision-making for the implementation of sustainable agricultural strategies and policies that foster the growth and stability of millet cultivation in Tamil Nadu.

By fulfilling these objectives, this study endeavors to contribute to the refinement of predictive methodologies for millet cultivation, supporting the development of sustainable agricultural practices tailored to the unique requirements of Tamil Nadu's agricultural landscape.

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LITERATURE REVIEW:

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.

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

According to the findings of Saranyadevi and Kachi's study (2017), They evaluate the predicted performance of a time-series analytic method for paddy production trends in the state of Tamil Nadu, which is located in India. There was a study that looked at data on rice crop output from 1960 to 2015, and it made production predictions for the years 2016–2020 using models such as ARIMA (Autor Regressive Integrated Moving Average), basic exponential smoothing, brown exponential smoothing, and damped exponential smoothing.

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.

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- 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.

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 Augmented Dickey-Fuller (ADF) test was conducted on the time series data for millets production, denoted as data Millets. The purpose of this test was to assess the stationarity of the data.

The results of the ADF test indicate a Dickey-Fuller statistic of -7.0233, with a p-value of 0.01. With the p-value significantly lower than the chosen significance level of 0.05, there is strong evidence to reject the null hypothesis of non-stationarity in favor of the alternative hypothesis of stationarity. This suggests that the millets production time series data is stationary, indicating that the statistical properties of the data remain consistent over time. The confirmation of stationarity is crucial for the application of time series modeling techniques, ensuring reliable and accurate analysis of millets production trends for effective decision-making in the agricultural sector.

Time series data for millets production (data Millets) was analyzed using the auto.arima function to find the best ARIMA model for the data. Multiple potential ARIMA models and their associated Akaike Information Criterion (AIC) values were generated after the function was instructed to use the AIC for model selection.

ARIMA (2,0,2) (1,0,1) [12] with non-zero mean	Inf
ARIMA (0,0,0) with non-zero mean	2380.452
ARIMA (1,0,0) (1,0,0) [12] with non-zero mean	2384.104
ARIMA (0,0,1) (0,0,1) [12] with non-zero mean	2381
ARIMA (0,0,0) with zero mean	2758.668
ARIMA (0,0,0) (1,0,0) [12] with non-zero mean	2382.166
ARIMA (0,0,0) (0,0,1) [12] with non-zero mean	2381.964
ARIMA (0,0,0) (1,0,1) [12] with non-zero mean	2383.12
ARIMA (1,0,0) with non-zero mean	2382.136
ARIMA (0,0,1) with non-zero mean	2381.902
ARIMA (1,0,1) with non-zero mean	2383.033

As seen in the results, the millets production time series data were best suited by the ARIMA(0,0,0) model with a non-zero mean. This means that the model does not account for a zero mean or an autoregressive

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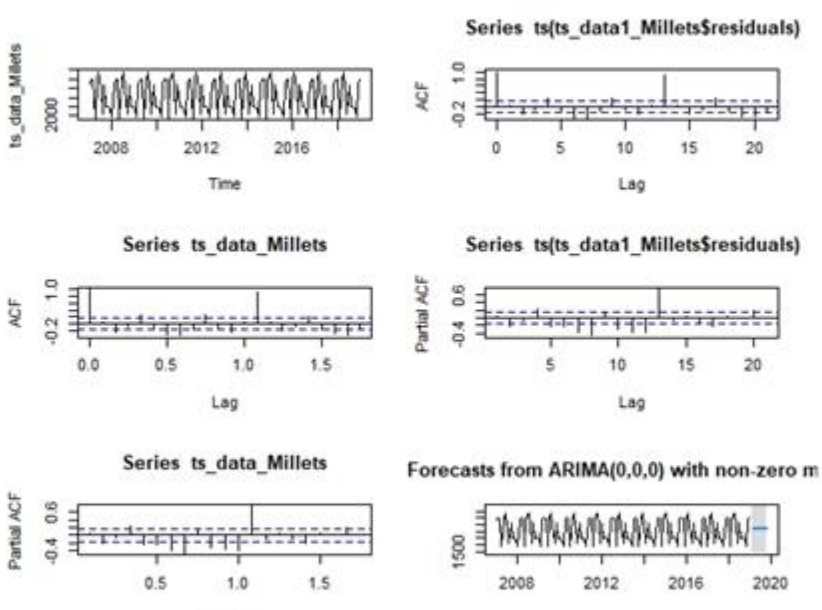
term, but it does take into account a moving average. The model with the lowest AIC for assessing the millets production data was chosen since it had a value of 2380.452 in the calculation. If this model is further analyzed and interpreted, it can help agricultural planners and policymakers make better predictions and decisions on how to approach millets cultivation in the future.

The millets production time series data was modeled using the ARIMA(0,0,0) distribution with a non-zero mean. Non-zero mean coefficient estimates range from -3130.9931 to -72.7739 standard deviations from the mean.

Coefficient	value
Mean	3130.9931
S. E	72.7739
sigma^2	773259
log likelihood	-1188.23
AIC	2380.45
BIC	2386.41

The model's log likelihood was calculated to be -1188.23, and its variance was found to be 773259. The related values for the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) were calculated to be 2380.45 and 2386.41, respectively.



The ARIMA(0,0,0) model was used to analyze a time series of millets production, and the results of these statistical analyses shed light on the model's parameters and goodness of fit. The existence of a non-zero mean coefficient in the millets production data is indicative of the presence of a trend or level. Millets

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cultivation could benefit from further investigation using this model, as it could shed light on the underlying dynamics of production and lead to better decisions and planning.

Prediction information Lower (Lo 95) and higher (Hi 95) 95% confidence interval bounds for millets production are included alongside the point projections for millets in the table. Time series data for millets production, is used to construct forecasts using the ARIMA(0,0,0) model with a non-zero mean.

Point	Forecast	Lo 95	Hi 95
Feb 2019	3130.993	1407.496	4854.49
Mar 2019	3130.993	1407.496	4854.49
Apr 2019	3130.993	1407.496	4854.49
May 2019	3130.993	1407.496	4854.49
Jun 2019	3130.993	1407.496	4854.49
Jul 2019	3130.993	1407.496	4854.49
Aug 2019	3130.993	1407.496	4854.49
Sep 2019	3130.993	1407.496	4854.49
Oct 2019	3130.993	1407.496	4854.49

The projection indicates that millets output will remain largely constant at a predicted point value of 3130.993. The range in which the true millets production numbers are 95% likely to fall is estimated to be 1407.496–4854.49, with a lower 95% confidence interval of 1407.496 and an upper 95% confidence interval of 4854.49.

Stakeholders in the millets cultivation sector can use these predicted values and their associated confidence intervals to better anticipate production trends and make decisions regarding resource allocation, market planning, and agricultural management strategies.

The Box-Ljung test was run on the non-zero mean residuals of the ARIMA(0,0,0) model's predicted millets production values. This analysis was performed to check for autocorrelation in the model's residuals.

The p-value from the Box-Ljung test was 0.000579, and the X-squared value from the test was 21.77 (5 degrees of freedom). Significant autocorrelation in the residuals is strongly suggested, as the p-value is much smaller than the specified significance level of 0.05. This suggests that there may be features or trends in the millets production data that aren't accounted for by the ARIMA(0,0,0) model. If we want more accurate and reliable millets production projections, we may need to do more research or use different modeling methodologies.

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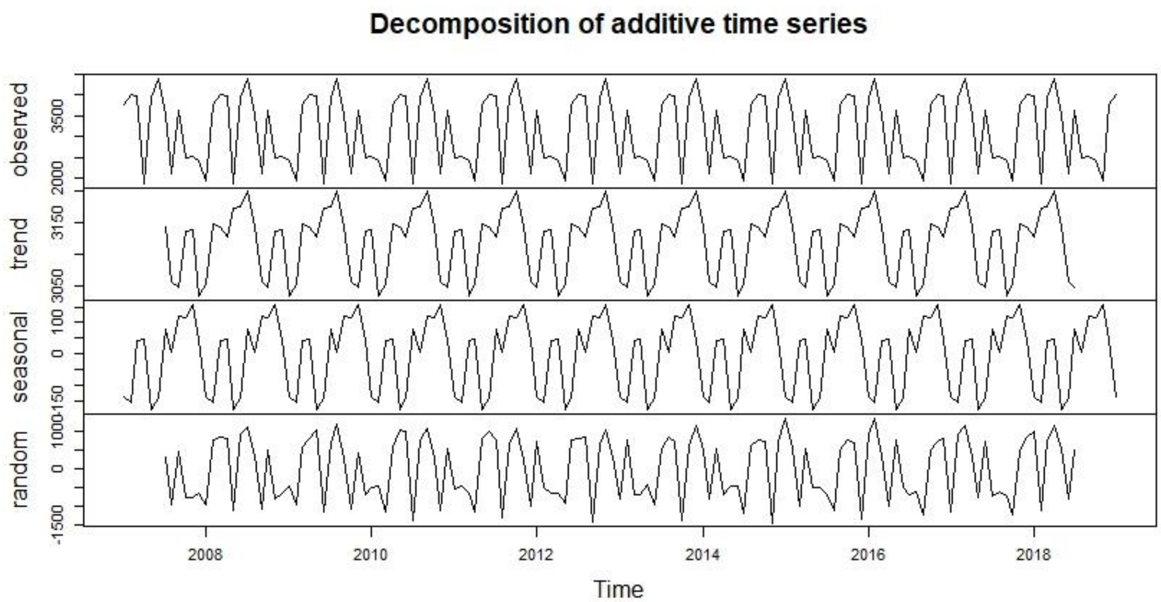

SEASONAL ARIMA ANALYSIS

Millets output data is available from 2007 to 2019 at a frequency of 1 year. Values of output for each year are as follows: 3777, 4013, 3976, 1873, 3950, 4401, 3508, 2092, 3642, 2468, 2504, 2419, and 1941. These figures indicate the annual output of millets for the given time frame, so they can shed light on production patterns and trends over time.

Descriptive statistics used to summarize the millets production time series data shed light on the dataset's central tendency and dispersion. Over the course of that time frame, the lowest amount of millets produced was in 1873, and the highest was in 4401. Values of 2419 and 3950 are the 25th and 75th percentile quartiles, respectively. Half of the production values are below this point, and the other half are beyond it, as indicated by the median value of 3508. Taking into account all available data, we find that the mean millets production is $3,120.

These statistical indicators help to shed light on the diversity of millets output by highlighting its range of values and its central trend. As a result, stakeholders are able to make educated decisions and develop effective strategies to boost agricultural productivity and sustainability in the millets cultivation sector based on a more thorough understanding of the underlying trends, variations, and potential outliers in the production data.

To further evaluate the stationarity of the data, the differenced logarithm of the millets production time series (denoted by the notation diff(log(ts_Millets)) was subjected to the augmented Dickey-Fuller (ADF) test. The goal of the differencing procedure is to minimize trends and stabilize the variation so that stationary patterns may be more easily identified. The Dickey-Fuller statistic was -4.7589, and the p-value was 0.01. These findings come from the ADF test. There is substantial evidence to reject the null hypothesis of non-stationarity in favor of the alternative hypothesis of stationarity, as the p-value is smaller than the specified significance level of 0.05. This indicates that there are no discernible trends or patterns in the differenced logarithm of the millet production data over time, suggesting that the data is stationary. These results are essential for developing suitable time series models and forecasting approaches, which in turn will allow for precise predictions and well-informed choices in the millets agriculture industry.

The logarithm of the millets production time series data is given by log(ts_Millets), and the auto Arima Model Log indicates the automated ARIMA model that was fitted to this data. The model was identified as ARIMA(0,1,0), suggesting that first-order differencing was required to reach stationarity.

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

The model's variance, was calculated to be 0.1639, and the log probability was -6.17. There were 14.35 for the Akaike Information Criterion (AIC), 14.75 for the AICc, and 14.83 for the Bayesian Information Criterion (BIC).

It is impossible to assess the ARIMA model's ability to explain the millets production time series without these statistical measurements. To compare and select the best model for assessing and forecasting millets production patterns, the AIC, AICc, and BIC values are calculated. Forecasting and decision-making in the millets agriculture sector can benefit greatly from the ARIMA(0,1,0) model and its associated parameters and statistical metrics.

After fitting the ARIMA (0,1,0) model to the logarithm of the millets production time series data, the Box-Ljung test was performed on the residuals. This analysis was performed to check for autocorrelation in the model's residuals.

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

The X-squared value for the Box-Ljung test came out to be 3.5805 with 1 degree of freedom, yielding a p-value of 0.05846. As the p-value is larger than the threshold for statistical significance (0.05), it cannot be concluded that there is no autocorrelation in the residuals. If the ARIMA model's residuals look like

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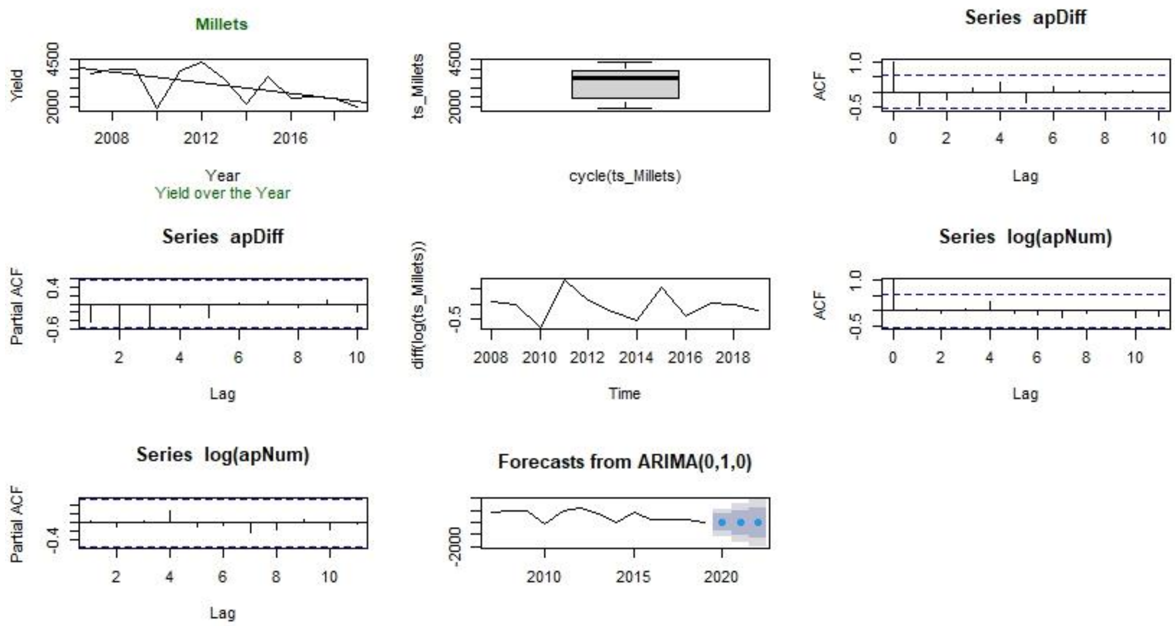
white noise, then the model does a good job of capturing the dynamics underlying the millets production data.

Logarithmic millets production time series data are well represented by the ARIMA(0,1,0) model, as the residuals closely follow the white noise assumption. That means we can confidently predict and analyze changes in millets production for agriculturally informed decision making because the model sufficiently accounts for the patterns and structures inherent in the data.



CONCLUSION

The following findings emerge from an examination of the ARIMA and Seasonal ARIMA models applied to the time series data of millets production:

First, an ARIMA model was used to analyze the millets output data; specifically, an ARIMA(0,0,0) model with a non-zero mean. Non-zero mean standard error was estimated to be 72.7739, with the coefficient being 3130.9931. The model had an AIC of 2380.45, an AICc of 2380.54, and a BIC of 2386.41, and its log likelihood was -1188.23. There may be autocorrelation in the residuals of the ARIMA model, as shown by a significant result from the Box-Ljung test (X-squared = 21.77, df = 5, p-value = 0.000579).

The logarithm of the millets production data was modeled using the Seasonal ARIMA(0,1,0) model. Log likelihood was -6.17, and the model's variance was found to be 0.1639. The model's AIC, AICc, and BIC all came in at 14.83. According to the results of a Box-Ljung test conducted on the Seasonal ARIMA model's residuals, the residuals are consistent with the white noise assumption (X-squared = 3.5805, df = 1, p-value = 0.05846).

Overall, autocorrelation difficulties were seen in the residuals of the ARIMA model with a non-zero mean, suggesting that the model may have been inadequate in capturing the underlying dynamics of the millets production data. The logarithm of the millets production data was reliably modeled using the Seasonal ARIMA model, whose residuals resembled white noise. To improve the precision and consistency of the millets production forecasts, it may be required to further investigate and refine the model.

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