Using the Box-jenkins Autoregressive Integrated Moving Average Method in Cabbage Production Forecasting

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Abstract. The research objective was to predict cabbage (*Brassica oleracea* L.) production using Box-jenkins autoregressive integrated moving average (ARIMA) method. This method is suitable in time series data with observational values that are statistically related to one another. Cabbage is one of the main agricultural commodities in Batu city, with a productivity of 180 quintals per hectare in year 2022. Based on the economic potential of the cabbage crop which is quite high, forecasting the production of cabbage is necessary to optimize inventory management and supply planning. The data used on monthly cabbage yield in Batu for the last five years from January, 2018 to December, 2022 which is 60 observations as the basis for analysis. The analysis result shows that the best model for prediction cabbage production is ARIMA (1,0,0) and forecasting result for the next twelve months shows a constant pattern. The model produces a MAPE value of 6.09% means that the accuracy of the model is 93.91% so, it can be concluded that the model is suitable for use in the analysis of cabbage production data. The results of this study are expected to provide valuable insights for farmers, traders and other related parties in optimizing the production, distribution and marketing strategies of cabbage in Batu city.

Keywords: ARIMA, cabbage, forecasting, MAPE, time series

Introduction

The Box-jenkins model is one of the break throughs of the contemporary approach to time series data analysis (Nyomi, 2018). Both stationary or non-stationary with or without seasonal elements can appropriately grasp with this method. The Box-jenkins ARIMA approach is used in an analytical method on univariate data used in forecasting with good accuracy for short term forecasting (Farimani *et al*., 2022). The ARIMA method predicts the value of a variable in the future using the value of the variable itself in the past and present (Wirawan *et al*., 2019). This method is suitable if the observed values of a time series are statistically related to one another.

Research involving ARIMA model was carried out by Oliveira *et al*. (2019), resulting that the modeling is a useful tool for recommending fertilization for cabbage and is subject to constant improvements. Previous research conducted Elvani *et al*. (2016), that used the ARIMA method to forecast PT NIKP Kutai Timur's oil palm production and the result is that the most suitable model was the ARIMA model (3,1,1). A similar study conducted by Bangun (2016) which gave the results of the ARIMA (0,1,1) model which is suitable for predicting soybean production in north Sumatra province. Other research by Nath *et al*. (2019), concluded that ARIMA (1,1,0) model was found to be the best ARIMA model in forecasting the future wheat production for a period upto ten years as accurate as possible. The forecast results have shown that the annual wheat production will grow in 2026-27 with an average growth rate of approximately 4% per year. Research by Akhi *et al*. (2021), concluded that the most suitable model for predicting cabbage production in Bangladesh is ARIMA (1,2,3).

Batu city is one of the city in east Java province which has three main pillars to support the economy, namely the agricultural sector, the tourism sector and MSMEs. The total agriculture area in Batu city is 1,998.44 hectares with 76.81% used for cultivating horticultural crops and the rest is for cultivating rice plants. There are 26 agricultural commodities developed in Batu city including vegetables and fruits ranging from shallots, cabbage, radishes, long beans, mushrooms, to strawberries. Cabbage is an economically productive crop produced in Batu city. However, over the last 6 years there has been a decline in the productivity of cabbage plants in Batu city. In 2017 farmers in Batu city were able to produce 7162.40 tons of cabbage but this decreased every year until 2022, cabbage production

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in Batu city only reached 246 tons. Research conducted by Zamrodah (2020), to analyze the feasibility and profitability of cabbage farming in Beji village, Junrejo, Batu city. This study involved 30 cabbage farmers and used primary and secondary data. The research results show that cabbage farming in Beji village is feasible and profitable, with an R/C value of 2.61. Cabbage farmers can earn an income of Rp. 53,473,500 in one harvest.

The production of cabbage in Batu city area is one of the things that needs to be considered in order to maintain market demand fulfillment and support the welfare of farmers and the sustainability of the regional economy. The cabbage production forecasting is needed in inventory management and supply planning. With an accurate estimate of the future of cabbage production, farmers and traders can make more informed decisions in terms of cabbage planting including factors that would be increasing the cabbage production. In addition, the Batu city agriculture and food security service can obtain material for consideration in making policies and making appeals to cabbage farmers.

Agricultural production modeling and forecasting play pivotal roles in informing policy decisions, enhancing agricultural productivity and ensuring food security. Across various regions and crops, researchers have employed diverse methodologies to analyze historical trends, anticipate future outcomes and identify factors influencing production dynamics.

In south Asian countries, studies such as Mishra *et al*. (2023) and Yadav *et al*. (2022), have focused on modeling and forecasting pulses and maize production, respectively. These research endeavors integrate statistical analysis and time series modeling, such as ARIMA, neural network and state-space model. To provide insights into production trends, seasonal variations and socio-economic influences. By leveraging empirical data and analytical tools, these studies contribute to enhancing our understanding of crop dynamics and informing evidence-based interventions in the agricultural sector.

In India, the COVID-19 pandemic has spurred research efforts to model and forecast disease transmission dynamics, as demonstrated by Mishra *et al*. (2020) and Rahman *et al*. (2022). These studies utilize epidemiological models and statistical methodologies (ARIMA and SARIMA) to analyze case data, assess the effectiveness of control measures and anticipate healthcare demands. Jafarian *et al*. (2024) focuses on the modeling and foreasting the air temperuture in Tehtan by comparing the ARIMA and SARIMA to capture the autocorelative structure in the tempurature data.

By providing timely insights and scenario analyses, these studies aid policymakers and healthcare professionals in formulating response strategies and mitigating the impact of the pandemic on public health and socio-economic well-being.

Furthermore, the literature extends to horticultural crops, as evidenced reported by Ray *et al*. (2023) and Yadav *et al*. (2022). These studies employ econometric approaches and statistical modeling such as exponential smoothing, ARIMA and state space model, to predict fruit and maize production, respectively. By incorporating economic indicators, climatic variables and agronomic practices, these studies offer valuable insights into production dynamics, market trends and supply chain management in the horticultural sector.

In animal husbandry, research such as Yonar *et al*. (2022), focuses on modeling and forecasting milk production in different cattle breeds in Turkey. By integrating breed-specific data and statistical analysis. This study enhances our understanding of milk production dynamics and informs breeding programs, nutrition management and dairy industry strategies in Turkey. The results of this study showed that the bes predicts are obtained by ARIMA model.

In summary, the diverse array of research endeavors in agricultural production modeling and forecasting underscores the multidisciplinary nature of agricultural sciences. By integrating empirical data, advanced methodologies and interdisciplinary approaches, these studies contribute to addressing challenges, optimizing resource allocation and promoting sustainable agricultural development globally. Continued research, collaboration and innovation are essential for advancing predictive modeling capabilities, improving data quality and fostering resilience in agricultural systems amidst evolving environmental, economic and social dynamics.

Materials and Methods

The secondary data used is monthly cabbage production in Batu city from January, 2018 to December, 2022 which is 60 observations that obtained from the Department of Agriculture and Food Security of Batu city.

ARIMA. Descriptive statistics is used in describing the data so that it is easy to understand. Several ways to describe data are using data concentration measures such as the average and using data distribution measures such as variance and range.

The data is said to be stationary with respect to the variance if the value λ = 1 or close to 1. If the data is not stationary with respect to the variance and has a positive value, then the Box-Cox transformation can be carried out as (Wei, 2006): $T(X_t)=\frac{X_t^{\lambda}}{\lambda}$.

Stationarity in mean can be detected by the Augmented Dickey-Fuller (ADF) unit root test. The basic equation of the test is (Gujarati and Porter, 2009):

$$X_t=\phi X_{t-1}+a_t,\ -1\leq \phi \leq 1$$

If the stationary of the mean is not fulfilled then the differentiation process can be carried out with the order d as follows:

$$\Delta^d X_t = (1-B)^d X_t$$

The auto-correlation function is used to see whether there is a correlation in the same data from one time to another. The equation for the auto-correlation function of data with log k (Wei, 2006) is as follow:

$$\hat{\rho}k = \frac{\Sigma_{t=1}^{n-k} (x_t - \overline{x})(x_{t+k} - \overline{x})}{\Sigma_{t=1}^{n} (x_t - \overline{x})^2}$$

The partial auto-correlation function (PACF) measures the correlation between X_t dan X_{t+k} regardless of the independence $X_{t+1},\ldots, X_{t+k-1}$. The calculation formula for the same time index is:

$$\hat{\phi}_{k+1,k+1}=\frac{\hat{\rho}_{\kappa+1} - \Sigma_{j=1}^{k} \hat{\phi}_{\kappa j}\, \hat{\rho}_{\kappa+1-j}}{1- \Sigma_{j}^{k}\ \phi\, k_j\, \hat{\rho}_j}$$

While the formula for different time indexes is $\hat{\phi}_{kj} = \phi_{k-1,j} - \hat{\phi}_{kk}\, \hat{\phi}_{k-1,k-j}$

The auto-regressive integrated moving Average (ARIMA) is a model that completely ignores independent variables in making forecasts and assumes that the time series data used must be stationary (Wei, 2006), while the ARIMA model (p,d,q) can be written as $\phi_p (B)(1-B)^d X_t= \theta_q (B)a_t$.

One method of parameter estimation is the maximum likelihood method which has the principle of maximizing the likelihood function. The maximum likelihood method has the advantage of not requiring many requirements compared to the least squares method which requires the model to be linear in parameters and so on.

After the provisional model is identified, the next step is to test whether the parameters obtained are feasible to be used in the model using the t test. Knowing the residuals assumption of white noise (no autocorrelation) is done by the Ljung-box test, while testing for the normality of the distribution used the Anderson-darling test.

Box-Jenkins procedure. Box and Jenkins (1976), popularized the use of ARIMA models through the following three steps (Makridakis and Hibon, 1997). The first one is model identification, the step involves determining the order of the model required to capture the dynamic features of the data. Graphical procedures are used (plotting the auto-correlation function (ACF) and partial ACF (PACF) of the time series) to decide which (if any) AR or MA component should be used in the model. To achieve this, first ARIMA needs to be stationary, that it should have a constant mean, variance and auto-correlation through time. Since the data are non-stationary, we have to transform the series to induce stationarity. And then parameter estimation, this step involves estimating the parameters of the models specified in model identification step. Computational algorithms (least squares or another technique, known as maximum likelihood) are used to arrive at coefficients which best fit the selected ARIMA model. The last is diagnostic checking, this step is to test whether the model specified and estimated is adequate. Box and Jenkins suggest two methods: over fitting and residual diagnostics. Over fitting involves deliberately fitting a larger model than that required to capture the dynamics of the data as identified in step one. If the model specified at step one is adequate, any extra terms added to the ARIMA model would be insignificant. Residual diagnostics implies checking the residuals. The residuals should be white noise or (independent when their distributions are normal) drawings from a fixed distribution with a constant mean, variance and un-correlated with each other. (Plotting auto-correlation and partial auto-correlation of the residuals are helpful to identify mis-specification.) If the model is found to be inadequate, it is necessary to go back to step two and try to identify a better model.

Model selection. The best model is selected using Akaike's information criterion (AIC) by considering parameters in the model. Forecasting that is an activity to predict future conditions using past information or data from one or more variables, the can be measured using the mean absolute percentage error (MAPE) criteria with the formula:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|x_t - x_t|}{x_t}$$

Cabbage (*Brassica oleracea* L.) is an annual or two-season crop (Kehulinta, 2020). The shape of the leaves is oval to oval and wide like a fan. Cabbage contains fiber, minerals (Ca, P and K), Vitamins (C, K, A and folate) and large number of secondary metabolites (Uuh Narvaez and Segura Campos, 2021). Cabbage is suitable for planting in areas with cool air, at an altitude of 800–2000 meters above sea level and in a wet climate, such as Batu city. Soil suitable for growing cabbage is soil that contains lots of humus, loose, porous, with a pH of 6–7.

Results and Discussion

Cabbage production fluctuates every month. For this reason, before conducting the analysis, it is necessary to know the characteristics of cabbage production in Batu city from 2018 to 2022. The characteristics of cabbage production data in the city of stone are shown in Table 1.

It is seen that most of the cabbage production is around 3,888 quintals per month. The maximum is 5,823 quintals that occurred in February, 2019. This was influenced by the large planting area in Batu city, which was 33 hectares in area. The deviation value indicate that cabbage production per month is around 3,045 quintals to 4,731 quintals. Then plotting of the data in months (January, 2018 to December, 2022) is presented in Fig. 1.

Table 1. Descriptive statistics of cabbage production in Batu from 2018 to 2022

Description	Production (Quintal)
Minimum	1,636
Mean	3,888
Maximum	5,823
Std. deviation	0.843
Interval	4,187

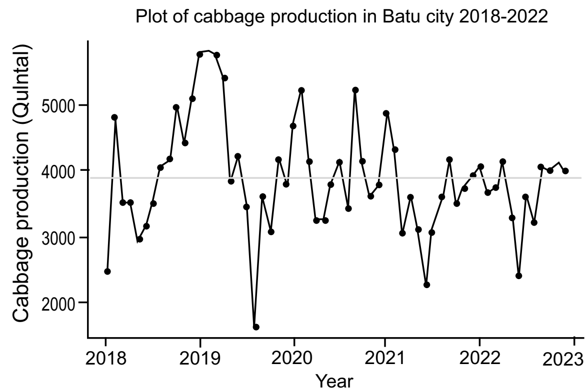

Fig. 1. Data plot monthly of cabbage production in Batu from 2018 to 2022.

Cabbage production every month tends to form a random pattern around the average value, there is no linear pattern which indicates the data is stationary with respect to the mean. Data fluctuations that are not too extreme indicate that the data is stationary with respect to variance. To ascertain whether the data is truly stationary with respect to variance and mean, lambda criteria and the ADF test are used.

Data stationarity. In data on monthly cabbage production in Batu city for the period January, 2018 to December, 2022, a value of $\lambda=1$ is obtained, which means that the data is stationary with respect to variance. Then the ADF test was carried out and the ADF test statistic was -3.5155 which was smaller than the ADF critical point -3.49. The P-value obtained is 0.0479 which is smaller than the alpha significance level of 0.05, it is concluded that the data is stationary with respect to the average.

ARIMA Model identification. To determine the tentative model, the ACF and PACF plots are used as presented in Fig. 2 and 3.

Based on Fig. 2 and 3, it appears that two lags cross the boundary in a row on the ACF plot and one lag crosses the boundary on the PACF plot, so there are five tentative models that will be formed, namely ARIMA (1,0,2), ARIMA (1, 0,1), ARIMA (1,0,0), ARIMA (0,0,2) and ARIMA (0,0,1). From these five

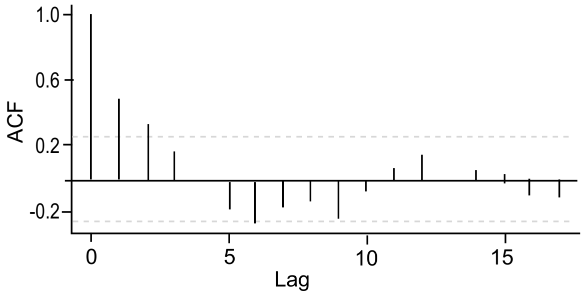

Fig. 2. ACF Plot of cabbage production model in Batu from 2018 to 2022.

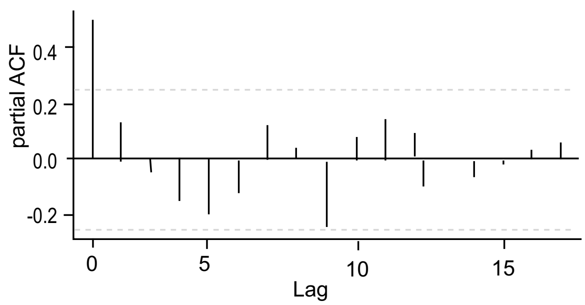

Fig. 3. PACF Plot of cabbage production model in Batu from 2018 to 2022.

Table 2. Coefficients of ARIMA models

Model	Parameter estimation	Coef.	P-value
ARIMA (1,0,2)	$\hat{\varphi}_1$	0.5586	0.008
	$\hat{\theta}_1$	-0.1336	0.5745
	$\hat{\theta}_2$	0.1122	0.4723
ARIMA (1,0,1)	$\hat{\varphi}_1$	0.6207	0.0002
	$\hat{\theta}_1$	-0.1582	0.4397
ARIMA (1,0,2)	$\hat{\varphi}_1$	0.5054	$7.39\text{x}10^{-6}$
ARIMA (1,0,2)	$\hat{\theta}_1$	0.4300	0.0012
	$\hat{\theta}_2$	0.2462	0.0372
ARIMA (1,0,2)	$\hat{\theta}_1$	0.3985	0.0001

Table 3. Ljung-box test

Model	Statistical test	Critical value	P-value
ARIMA (1,0,0)	0.3588	6.5706	0.5491
ARIMA (0,0,2)	0.0132	5.8918	0.9085
ARIMA (0,0,1)	0.3276	6.5706	0.5671

model candidate, it should be checked the parameter estimate of each model whether in p, d or q model is adequate enough.

ARIMA Model parameter estimation. After identifying the model, it is followed by parameter estimation using the maximum likelihood method and parameter significance testing using the t test as shown in Table 2.

Based on Table 2, all parameter estimators in the ARIMA(1,0,0), ARIMA(0,0,2) and ARIMA(0,0,1) models generate a P-value t test result that is smaller than 0.05. It can be concluded that the three models have parameters with significant influence and are suitable for use in modeling.

In testing the non-autocorrelation assumptions of residuals or white noise using the Ljung-Box test produces test statistics and P-values as shown in Table 3.

The ARIMA(1,0,0), ARIMA(0,0,2) and ARIMA(0,0,1) models produce a statistical value of the Q test that is less than the critical point, the P-value of the Ljung-box test results is more than 0.05 so it is concluded that the three ARIMA models have fulfilled the white noise residual assumption.

To test the fulfillment of the assumption of normality of the residuals, the Anderson-darling test is used. The value of the test statistics along with the P-value of the Anderson-darling test are as follows in Table 4.

The Anderson-darling test on the three ARIMA models yields a statistical values that less than the critical point AD0,05=0,7514 and the P-values are greater than the alpha significance level of 0,05 so the conclusion is tthat the distribution of residuals in ARIMA(1,0,0), ARIMA(0,0,2) and ARIMA(0,0,1) models follow the normal distribution.

Among those three models with parameters that have a significant effect and the assumptions of normality and residual white noise are fulfilled, the best model will be selected based on the Akaike information criterion (AIC) value as presented in Table 5.

The smallest AIC found in the ARIMA (1,0,0) model, so this model is then used for forecasting. The model

Table 4. Anderson-darling normality test

Model	Statistical test	P-value
ARIMA(1,0,0)	0.2260	0.8819
ARIMA(0,0,2)	0.4513	0.3823
ARIMA(0,0,1)	0.4220	0.4516

Table 5. AIC statistics

Model	AIC
ARIMA(1,0,0)	966.6140
ARIMA(0,0,2)	969.7778
ARIMA(0,0,1)	971.6045

obtained is ARIMA(1,0,0) with the following equation is$X_t = 0{,}5089\ X_{t-1}+\alpha_t$. Cabbage production in Batu city was influenced by cabbage production in the previous period. The MAPE value is 6.09%, which means the accuracy of the model is 93.91% so that the model is suitable for forecasting cabbage production. Plots of cabbage production data for the 2018-2022 period along with forecasting results for the 2023 period are presented in Fig. 4.

The data pattern resulting from forecasting cabbage production for the next twelve months tends to form a constant pattern. The forecasted values for the twelve periods along with the actual values upto July, 2023 are presented in Table 6.

Forecasting results of cabbage production in Batu city tend to be constant with the highest production yield predicted in January, 2023 of 3,929 quintals, while the lowest production yield in December, 2023 of 3,866 quintals.

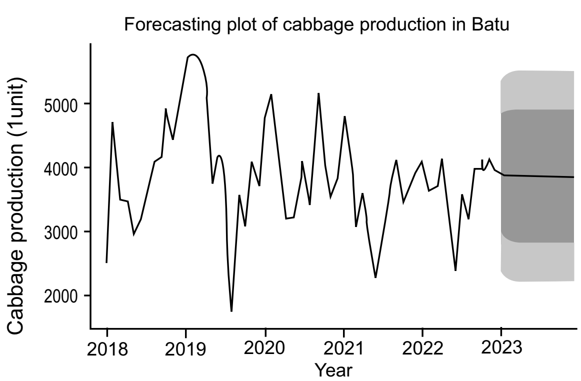

Fig. 4. Actual plot and data prediction.

Table 6. Prediction of cabbage production

Month (in 2023)	Forecast (quintal)	Actual (quintal)
January	3,929.013	3,620
February	3,897.925	3,752
March	3,882.213	4,184
April	3,874.272	3,766
May	3,870.258	3,503
June	3,868.230	4,133
July	3,867.204	3,707
August	3,866.686	
September	3,866,424	
October	3,866.292	
November	3,866.225	
December	3,866.191	

Conclusion

The conclusions that can be drawn from this research are The most suitable ARIMA model for predicting cabbage production in Batu city is ARIMA (1,0,0). cabbage production in Batu city was influenced by production in the previous period. This information can be used as a support that stakeholders are paying attention to the important factors that support the increase in cabbage production forecasting results of cabbage tends to be constant with the highest production predicted in January, 2023, while the lowest production is in December, 2023. Based on the prediction results, it can be concluded that with constant conditions like previous years, cabbage production in Batu city will not experience a significant increase or decrease. Government intervention is needed for cabbage farmers to help farmers increase cabbage production in the following years.

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Conflict of Interest. The authors declare they have no conflict of interest.

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