Volume 2 June (2026)

The 2nd FORSTAT International Conference

Forecasting Wholesale Rice Prices in Indonesia Using an ARIMAX Model with ENSO and Hydrometeorological Disaster Variables

Nadya Ilma Pratiwi

Computer Science Faculty, UPN Veteran Jawa Timur, Indonesia

*Corresponding author: nadyailmap@gmail.com

ABSTRACT

Rice is the main staple food in Indonesia, making its price stability a critical component of national food security. However, rice prices often fluctuate due to various factors, including climate variability and hydrometeorological disasters. One of the global climate drivers affecting agricultural conditions is the El Niño–Southern Oscillation (ENSO), which influences rainfall patterns and crop productivity. In addition, disasters such as floods and droughts can disrupt production and distribution, thereby affecting wholesale rice prices. This study aims to forecast wholesale rice prices in Indonesia using the Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) model by incorporating ENSO indicators and hydrometeorological disaster variables. Monthly data from January 2015 to February 2026 were analyzed through stationarity testing, model identification, and parameter estimation, followed by model evaluation using Mean Absolute Percentage Error (MAPE). The results show that the best model is ARIMAX(1,1,0), which produces a MAPE value of 3.42%, indicating highly accurate forecasting performance. Despite this high accuracy, the influence of ENSO and disaster variables is relatively weak and occurs with a time lag, suggesting that rice prices are more strongly driven by internal market dynamics. These findings highlight that while climate and disaster factors contribute to price variations, their impact is limited in the short term.

Keywords: ARIMAX; Rice Price Forecasting; ENSO; Hydrometeorological Disasters; MAPE

1. Introduction

Rice is a staple food that plays a crucial role in national food security. As the staple food for the majority of the population, the stability of rice availability and prices are important indicators for maintaining macroeconomic stability and public welfare. Insufficient food availability can trigger economic instability, making rice price stability a crucial aspect in maintaining economic stability and public welfare [1]. Rice price dynamics in Indonesia are not solely influenced by the supply-demand balance, so even stable production can cause rice prices to rise. This situation indicates that rice price formation is not solely influenced by production factors or supply-demand mechanisms, but also by other factors such as policy, distribution, and external factors, including vulnerability to climate change [2].

As an archipelagic country, Indonesia is highly vulnerable to climate change. Global phenomena such as the El Niño–Southern Oscillation (ENSO) are a major factor influencing climate variability in Indonesia, particularly rainfall patterns. ENSO is associated with changes in sea surface temperatures,

Copyright: © 2026 by auhtors.
This is an open access article under the CC BY-SA license.

which cause seasonal shifts in Indonesia. During El Niño conditions, rainfall tends to decrease, increasing the risk of drought and limited irrigation water. Meanwhile, La Niña causes increased rainfall, potentially causing flooding in agricultural areas. These conditions impact the agricultural sector, such as disrupting planting schedules and the risk of crop failure, which can ultimately lead to decreased agricultural production [3]. The variability of rainfall influenced by the ENSO phenomenon not only impacts rainfall amounts but also its temporal distribution throughout the year. High rainfall variations can lead to uncertainty in determining planting times, especially on agricultural land that is highly dependent on rainfall availability [4]. This condition makes it difficult for farmers to determine the start of the planting season and increases the risk of a mismatch between crop water needs and environmental conditions. Furthermore, rainfall anomalies due to climate variability also impact planted area, harvested area, and rice yields. These disruptions not only directly affect production volumes but also have the potential to cause instability in the food supply. More broadly, these production dynamics can have implications for market price formation. This condition reinforces the finding that rice prices are influenced not only by production factors but also by structural factors such as distribution and policy [2].

Hydrometeorological disasters are one of the tangible impacts of climate change that are increasingly occurring in Indonesia, particularly in the form of floods, droughts, and other extreme weather events. Increased rainfall intensity and changing climate patterns have triggered more frequent flooding, while longer dry periods increase the risk of drought in the agricultural sector [5]. In general, most natural disasters in Indonesia are dominated by hydrometeorological disasters triggered by climate variability and extreme weather [6]. This condition places significant pressure on the agricultural system, given that this sector is highly dependent on stable climate factors. Climate change not only increases the frequency of disasters but also directly impacts crop productivity through disruptions in water availability, changes in planting seasons, and an increased risk of crop failure [7].

Previous research has shown that rice price analysis in Indonesia is still dominated by partial approaches, both in terms of policy and quantitative methods. A study by Annaji et al. emphasized that rice price fluctuations are influenced by complex factors such as government policy, distribution, production, and import dependence [8]. However, this study used a qualitative approach based on literature studies and therefore was unable to empirically measure causal relationships or quantitative contributions between variables. On the other hand, research by Naya et al. has implemented an ARIMA model for rice price forecasting and indicated the influence of climate factors such as El Nino, but these variables were only used to interpret the results, not as exogenous variables explicitly modeled in the forecasting framework [9]. Meanwhile, a climate-related study by Ariska et al. showed that the ENSO phenomenon is related to rainfall variability and impacts the agricultural sector, but this study did not directly link these impacts to the price dynamics of food commodities such as rice [10]. Thus, there is a significant research gap in the form of the lack of integration between global climate variables (ENSO), hydrometeorological impacts, and economic factors in a quantitative model that can explain and predict rice prices more comprehensively. Therefore, this study contributes by developing an ARIMAX model that integrates climate variables as exogenous factors to improve forecasting accuracy while providing a deeper understanding of the influence of climate on rice price dynamics in Indonesia.

Based on these issues, this study aims to develop a rice price forecasting model in Indonesia using the Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) approach. This model integrates ENSO variables and hydrometeorological disaster data, such as floods and droughts, as external variables to improve forecast accuracy. This research is expected to produce results that can provide a more comprehensive understanding of the influence of climate variability on rice price dynamics.

2. Theoritical Framework

2.1. El Nino–Southern Oscillation (ENSO)

The El Nino–Southern Oscillation (ENSO) phenomenon is one of the major global climate variability that occurs due to the interaction between the atmosphere and the ocean in the tropical Pacific Ocean. ENSO is characterized by the presence of sea surface temperature (SST) anomalies in the Niño 3.4 region which are then classified into two main phases, namely El Nino (warming phase) and La Niña (cooling phase) [11]. This phenomenon affects global atmospheric circulation so that it has a direct impact on the distribution of rainfall and climate conditions in the Indonesian region. In El Niño conditions, increased sea surface temperatures in the eastern Pacific cause reduced rainfall to the potential for drought, while in La Nina conditions encourage high rainfall [10]. In addition, ENSO also plays a role in controlling regional climate variability including sea surface temperature and rainfall which ultimately can trigger hydrometeorological events such as floods and droughts [12]. However, the influence of ENSO on certain environmental variables can vary spatially and is not always significant, depending on the characteristics of the region and interactions with other climate factors.

2.2. Hydrometeorological Disaster

Hydrometeorological disasters are a type of natural disaster caused by atmospheric and hydrological factors, such as changes in rainfall patterns, temperature, and climate dynamics that impact the air cycle on the Earth's surface. The most common forms of these disasters are floods and droughts, where floods generally occur due to extreme rainfall, insufficient drainage capacity, and river overflows, while droughts occur due to rainfall deficits in certain periods that disrupt air availability [13]. In Indonesia, hydrometeorological disasters dominate more than 80% of disaster events each year, which indicates the high vulnerability of tropical regions to climate variability and global climate change [14]. In addition, the phenomenon of climate change and atmospheric variability such as increased rainfall intensity and temperature anomalies also exacerbate the frequency and impact of floods and droughts, especially in urban areas with high environmental pressure [5]. Thus, hydrometeorological disasters are not only natural phenomena, but are also closely related to climate dynamics, environmental conditions, and human activities that affect the balance of the hydrological system.

2.3. Autoregressive Integrated Moving Average Exogenous

The Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX) model is an extension of the ARIMA model by adding exogenous variables [15]. In this model, the value of a dependent variable is influenced not only by its own past values (the autoregressive and moving average components) but also by other variables outside the relevant system.

$$(1-B)^d\, \phi_p(B)Y_t = \theta_q(B)\varepsilon_t + \beta_1 X_{1,t-k} + \beta_2 X_{2,t-k} + \cdots + \beta_k X_{k,t-k}$$

Keterangan:

Y_t= Dependent variable
B = Backshift Operator, with $BY_t = Y_{t-1}$
$\phi_p(B)$= Autoregressive (AR)
$\theta_q(B)$ = Moving Average (MA)
ε_t = Error at-t
$(1-B)^d$= Non-seasonal differencing operator
d = Orde of differencing
β_k = Parameter for exogenous variables
$X_{k,t-k}$ = Independent (exogenous) variable at time-$t-k$

The ARIMAX model still follows the basic steps of ARIMA, such as stationarity testing, model identification using ACF and PACF, and parameter estimation. The difference lies in the addition of additional variables integrated into the model.

2.4. Evaluation

The accuracy of the model in this study was evaluated using the Mean Absolute Percentage Error (MAPE). MAPE is used to measure the magnitude of the model's prediction error compared to the actual value, expressed as a percentage [16]. The smaller the MAPE value, the better the model's forecasting ability.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n} \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right| \times 100\%$$

Keterangan:

Y_t = Actual value in period-t
$\hat{Y}_t$ = Forecasted value in period-t
n = Number of observations
t = Time period

The MAPE value is then used to classify the model's forecasting ability. The criteria for assessing model accuracy based on the MAPE value are presented in the following table.

Table 1. MAPE Criteria

MAPE Value	Accuracy Category
< 10%	Highly Accurate
10% – 20%	Good Forecasting
20% – 50%	Reasonable Forecasting
> 50%	Inaccurate Forecasting

3. Methods

This study uses a quantitative approach with time series analysis to model and forecast wholesale rice prices in Indonesia. The model used is the Autoregressive Integrated Moving Average with Exogenous Variables (ARIMAX). The ARIMAX model was selected based on its ability to accommodate historical data patterns while integrating external variables, allowing for analysis of the influence of climate and disaster factors on rice prices.

3.1. Data Collection

The data used is monthly secondary data consisting of wholesale rice prices as the dependent variable, and ENSO as the independent variable, represented by the Oceanic Niño Index (ONI), as well as the number of floods and droughts. Data were obtained from the Central Statistics Agency (BPS), the National Oceanic and Atmospheric Administration (NOAA), and the National Disaster Management Agency (BNPB). All data were aligned to a monthly timeframe and aggregated based on the time variable.

3.2. Research Stages

The initial stage involved converting date variables to datetime format, which was then filtered starting from 2015 to ensure consistency across the analysis period. Descriptive statistical analysis was performed to understand the characteristics of the data, including the mean, standard deviation, minimum, and maximum values. In addition, a multicollinearity test was performed using the Variance Inflation Factor (VIF) to ensure that the independent variables did not have a strong linear relationship with each other. Correlation analysis was performed to determine the initial relationship between the variables. Next, the Cross-Correlation Function (CCF) was used to identify the lag effects of ENSO, floods, and drought on rice prices. Based on the CCF results, each exogenous variable was transformed into its optimal lag form for use in the ARIMAX model. Modeling was performed using ARIMAX by first ensuring data stationarity through the Augmented Dickey-Fuller (ADF) test. If necessary, differencing was performed. Data pattern identification was performed through Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) analysis. Modeling was performed using several candidate ARIMAX models with different parameter combinations (p, d, q). The model was trained using training data incorporating the lagged exogenous variables. Next, the forecasting process was performed on the testing data. The best model was selected based on the smallest error value, with MAPE as the main indicator of prediction accuracy.

4. Results and Discussion

This section presents the results of the analysis and discussion related to forecasting wholesale rice prices in Indonesia using the ARIMAX method with ENSO, flood, and drought variables. The data used is monthly data for the period January 2015–February 2026.

4.1. Correlation and Cross-Correlation Analysis

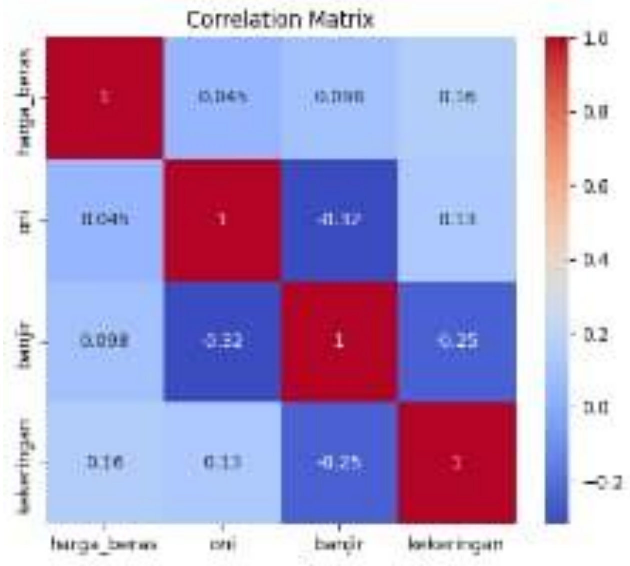

Figure 1. Correlation Matrix

The correlation matrix is presented in Figure 1. The correlation results show that the direct relationship between ENSO, floods, and droughts on rice prices is relatively weak ($|r| < 0.2$). This indicates that the influence of external variables is not direct. Next, a Cross-Correlation Function (CCF) analysis was performed, which shows the lag of each variable. The CCF results are as follows:

Table 2. Cross-Correlation Function Results

Variable	Lag	Correlation
ONI	6	0.37
Flood	11	0.08
Drought	6	0.28

This interpretation aligns with the mechanisms of the agricultural sector, where the impacts of climate change and disasters do not directly affect prices, but rather through the production, harvest, and distribution processes that require time. However, the relatively small correlation value indicates that, although there is a relationship, its influence is still limited.

4.2. Model Identification

The ARIMA model was determined by identifying data stationarity using the Augmented Dickey-Fuller (ADF) test.

Table 3. Stationary Test

Differencing	p-value	Status
0	0.77	Non-stationary
1	4.57e-15	Stationary

The Augmented Dickey-Fuller (ADF) test results indicate that the rice price data is non-stationary, as indicated by a p-value > 0.05. After differencing, the data became stationary. However, the p-value is close to 0, so the d value used to determine the best model is 0 or 1. Next, ACF and PACF plots were performed to determine the AR and MA values.

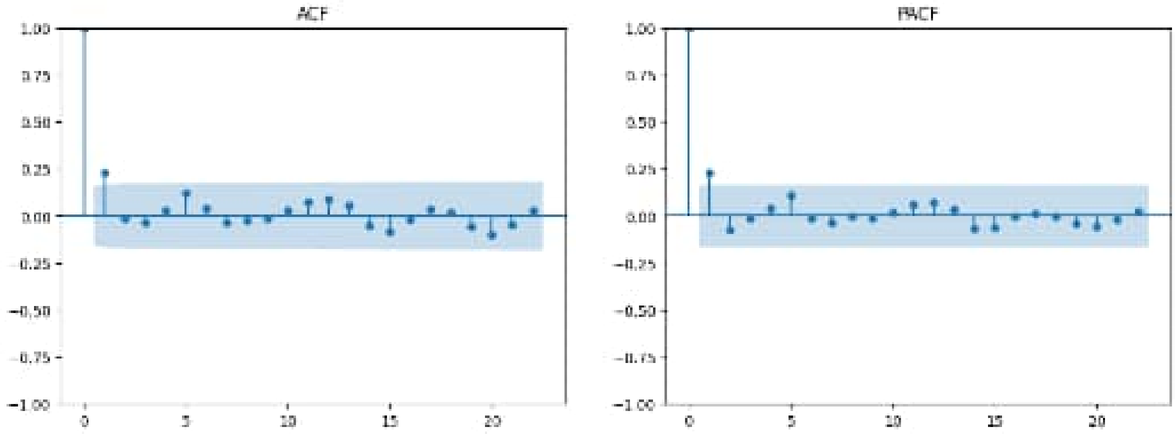

Figure 2. Plot ACF and PACF

Based on Figure 2, both showed a cut-off at lag 1, resulting in AR(1) and MA(1) values.

4.3. ARIMAX Model Selection

Table 4. Model Comparison

Model	AIC	MAPE
(0,1,1)	1500.23	3.91%
(1,1,0)	**1500.40**	**3.42%**
(1,1,1)	1502.17	3.64%
(0,0,1)	1680.43	16.54%
(1,0,0)	1509.92	5.92%
(1,0,1)	1506.43	6.30%

Based on Table 4, the ARIMAX(1,1,0) model was selected as the best model because it had the smallest MAPE value, although the AIC value was not the lowest. This indicates that the model has better predictive ability on the test data than the other models. The model produced a MAPE value of 3.42%, which is included in the highly accurate forecasting category. This quantitatively indicates that the model has excellent predictive ability for the test data. A residual test was conducted for the selected model to verify the presence of white noise.

Table 5. Residual Test

Test	p-value	Result
Ljung-Box	1.00	White Noise

The residuals have no autocorrelation, thus confirming the validity of the model. Residual non-normality is acceptable in economic data.

4.4. Forecast Result

Table 6. Testing Data Forecast Result

Period	Testing Data	Forecasting Data
2025-02	13604	13551.78
2025-03	13757	13568.86
2025-04	13728	13529.47
2025-05	13735	13529.93
2025-06	13979	13509.36
2025-07	14202	13513.74
2025-08	14292	13521.50
2025-09	14290	13524.19
2025-10	14264	13534.09
2025-11	14131	13559.91
2025-12	14162	13572.85
2026-01	14218	13624.89

Period	Testing Data	Forecasting Data
2026-02	14282	13562.86

Based on Table 6, it can be seen that the actual rice price data shows a gradual upward trend from the beginning to the end of the test period. Meanwhile, the forecast results from the ARIMAX model also show a pattern that tends to be lower than the actual data in several periods, especially when there are significant price increases. The model is able to follow the direction of data movement, but is not yet fully able to optimally capture price spikes. This indicates that the model is more effective at capturing trends than extreme fluctuations that occur in the short term.

Table 7. Forecast Result

Period	Forecast Result
2026-03	13558.53
2026-04	13561.97
2026-05	13562.68
2026-06	13562.83
2026-07	13562.86

Based on Table 7, the forecast results for the next period indicate that rice prices are expected to remain stable with very small increases. Changes in forecast values between periods are relatively small, indicating that the model projects stable market conditions without significant shocks. This pattern is consistent with the characteristics of the ARIMAX model, which emphasizes historical patterns rather than sudden changes caused by external factors. Furthermore, these results also indicate that the ENSO and hydrometeorological disaster variables used in the model have not yet exerted a strong influence on driving significant price changes in the short term.

5. Conclusion

The best model for forecasting wholesale rice prices using ENSO, drought, and flood variables is the ARIMAX(1,1,0) model. This model is capable of forecasting wholesale rice prices in Indonesia with a MAPE of 3.42%. However, the exogenous variables used have a weak correlation with rice prices, so their influence is indirect and relatively limited. The model is able to capture price trend patterns well, but is not optimal in representing extreme price spikes. This indicates that rice price dynamics are influenced not only by climate factors but also by other factors not included in the model. Thus, this study confirms that the ARIMAX approach is effective for rice price forecasting, but model development with the addition of other variables is needed to improve its predictive ability for more complex price dynamics.

REFERENCE

[1] M. Zaril Gapari, "Pengaruh Kenaikan Harga Beras Terhadap Kesejahteraan Petani Di Desa Sukaraja," 2021. [Online]. Available: https://ejournal.stitpn.ac.id/index.php/pensa

[2] I. M. Fahmid, M. Fahmid, A. Gemilang Badrani, and M. Magister, "The Impact of Indonesian Rice Policy: Production, Price, Import and Farmer's Welfare (2004-2024)," *JURNAL SOSIAL EKONOMI PERTANIAN*, vol. 21, no. 3, pp. 65–87, Oct. 2025, [Online]. Available: https://journal.unhas.ac.id/index.php/jsep

[3] N. Malay and Y. Situmorang, "Analisis Dampak ENSO Terhadap Variabilitas Curah Hujan di Daerah Irigasi Manganti Informasi Artikel," in *PROSIDING SEMINAR NASIONAL POLITEKNIK PEMBANGUNAN PERTANIAN BOGOR*, 2025, pp. 415–420. [Online]. Available: https://jurnal.polbangtan-bogor.ac.id/

[4] F. Aditya, E. Gusmayanti, and J. Sudrajat, "Pengaruh Perubahan Curah Hujan terhadap Produktivitas Padi Sawah di Kalimantan Barat," *JURNAL ILMU LINGKUNGAN*, vol. 19, no. 2, pp. 237–246, 2021.

[5] D. T. Tresnanti, A. Kurniadi, D. A. Puspito, P. Widodo, and K. Kusuma, "Komunikasi Bencana Sebagai Sistem Mitigasi Bencana Hidrometeorologi Akibat Perubahan Iklim di Jakarta," *PENDIPA Journal of Science Education*, vol. 8, no. 2, pp. 155–163, Jun. 2024, doi: 10.33369/pendipa.8.2.155-163.

[6] N. Amri Komarudin, C. Anam Afgan, and G. Nova Ardiantoro, “Pengetahuan dan Persepsi Rumah Tangga Tani di Perdesaan Terhadap Dampak Perubahan Iklim Pada Sektor Pertanian,” *Jurnal Ilmu Alam dan Lingkungan*, vol. 15, no. 2, pp. 24–32, 2024, [Online]. Available: https://journal.unhas.ac.id/index.php/jai2

[7] D. Ratnawaty Hakim, A. Rahmiwati, and R. Flora, “Menjelajahi Dinamika Pangan di Era Perubahan Iklim Terhadap Dampak di Indonesia dan Proyeksi Masa Depan: A Systematic Review,” *Journal of Multidisciplinary Research and Development*, vol. 7, no. 3, pp. 1703–720, 2025, doi: 10.38035/rrj.v7i3.

[8] M. Fatchul Annaji, M. Pratama, I. P. A. Weny, and P. D. A. Ohaq Lelangrian, “Analisis Kebijakan Terhadap Harga Beras Dalam Konteks Negara Vs Pasar Pada Ekonomi Politik,” *Journal of Society Bridge*, vol. 3, no. 1, pp. 1–9, Jan. 2025, doi: 10.59012/jsb.v3i1.60.

[9] F. Putri Naya, S. Sarah Berlianti, N. Parcha, and A. Kayla, “Peramalan Harga Beras Indonesia Menggunakan Metode Arima,” *INTELEKTIVA*, vol. 6, no. 2, pp. 184–93, Aug. 2024, [Online]. Available: https://www.jurnalintelektiva.com/index.php/jurnal/article/view/1063

[10] M. Ariska, H. Akhsan, M. Muslim, M. Romadoni, and F. S. Putriyani, “Prediksi Perubahan Iklim Ekstrem di Kota Palembang dan Kaitannya dengan Fenomena El Niño-Southern Oscillation (ENSO) Berbasis Machine Learning,” *JIPFRI (Jurnal Inovasi Pendidikan Fisika dan Riset Ilmiah)*, vol. 6, no. 2, pp. 79–86, Nov. 2022, doi: 10.30599/jipfri.v6i2.1611.

[11] I. N. Zulfa, A. Wirasatriya, and A. Ismanto, “Pengaruh ENSO Terhadap Variabilitas Curah Hujan Dan Klorofil-A di Perairan Samarinda,” *Jurnal Kelautan Tropis*, vol. 28, no. 2, pp. 277–287, Jun. 2025, doi: 10.14710/jkt.v28i2.22547.

[12] A. M. D. Asyam, B. Rochaddi, and R. Widiaratih, “Hubungan ENSO dan IOD terhadap Suhu Permukaan laut dan Curah Hujan Di Selatan Jawa Tengah,” *Indonesian Journal of Oceanography*, vol. 6, no. 2, pp. 165–172, May 2024, doi: 10.14710/ijoce.v6i2.17274.

[13] S. Y. Rahayu, A. Sari, and R. Utari, “Variasi Nilai Equivalent Water Height Di Indonesia dan Kaitannya dengan Bencana Hidrometeorologi (Banjir dan Kekeringan),” *Journal of Geodesy and Geomatics*, vol. 5, no. 1, pp. 65–74, 2025, doi: 10.23960/datum.v5i1.6821.

[14] A. G. Siregar, “Mitigasi Meningkatkan Kesadaran Risiko dan Penanggulangan Bencana Hidrometeorologi,” *Jurnal Riksa Cendikia Nusantara 2025*, vol. 1, no. 3, pp. 1–7, 2025, [Online]. Available: https://ejournal.lembagarisetmandirinusantara.or.id/index.php/jrcn/article/view/31

[15] N. Salsabila and A. Oktaviarina, “PERAMALAN PDRB DI JAWA TIMUR MENGGUNAKAN MODEL ARIMAX DENGAN VARIABELL EKSOGEN EKSPOR-IMPOR,” *Jurnal Ilmiah Matematika*, vol. 12, no. 1, pp. 208–218, 2024, doi: 10.26740/mathunesa.v12n1.p208-218.

[16] R. H. Silvia and Anneke Iswani Achmad, “Penerapan Metode ARIMAX dengan Efek Variasi Kalender pada Peramalan Harga Komoditas Cabai Rawit di Provinsi Jawa Barat,” *Bandung Conference Series: Statistics*, vol. 3, no. 2, pp. 689–698, Aug. 2023, doi: 10.29313/bcss.v3i2.9180.