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FORECASTING MODEL OF PRODUCTION AND PRICE OF GRAINS COMMODITY IN CENTRAL SULAWESI

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ABSTRACT

Food derives from biological resources, animals, and water, whether processed or not processed, meant as food or drink for human consumption. Food commodities have often been referred to as staples or basic needs of Indonesian people and others. The availability of staples has played a strategic role in stabilizing food security, economic security, and national political stability, leading to the issue of availability of staples receiving very serious attention from the Indonesia government. This study analyzed the best model of production forecasting and prices of rice and corn in Central Sulawesi, Indonesia. The study used the ARIMA method to predict the production and prices of rice and corn. The results of the analysis showed that the best model was the forecasting model of ARIMA rice production (4,0,0) with decreasing production forecast data trends and corn with the ARIMA model (1,0,0) with increasing production forecast data trends. The forecasting model of ARIMA rice price (2,2,0) with decreasing price forecast data trends and ARIMA corn prices (2,2,0) with increasing price forecast data trends.

Keywords: *Forecasting, Grains, Rice, Corn*

1. INTRODUCTION

Agriculture is an economic sector in Indonesia, both micro and macro. At the micro-level, agriculture provides the livelihood of the majority of the rural population, and at the macro-level it supports the manufacturing industry and ensures national food security. Food, by definition, is everything that comes from biological resources, animals, and water, whether processed or not processed, which is intended as food or drink for human consumption [1, 2]. Included in the definition of food are food additives, food raw materials, and other materials used in the process of preparing, processing, and/or making food and drink.

Food security is a condition of fulfillment of food needs – in this case, for all the Indonesian people. This has been reflected in the availability of sufficient food, both in quantity and quality, and affordable by people's purchasing power. Food commodities have often been referred to as staples or basic needs of Indonesian people. The availability of staples has played a strategic role in stabilizing food security, economic security, and national political stability, leading to the availability of staples receiving substantial attention from the government [3]. So far, there has been accurate and comprehensive information about the amount of staples consumption in Indonesia. Several calculation approaches of staples consumption based on various sources have indicated very diverse information. The national socio-economic survey as one of the information sources of staples consumption, though it has only been able to accurately capture processed staples consumption inside the household, while staples consumption of those processed outside the household has not yet been calculated accurately [4].

Staples are food materials that can be processed into food. The survey results of the Central Statistics Agency of Central Sulawesi showed that the most consumed staples were grains. The average consumption of the grains food group is 995,446 calories per capita per day [5]. The most consumed grains in the region were rice and corn [5].

Grains are sold freely in the market to meet their daily needs. Fulfillment of the need for grains has been one of the most important objectives both at the national and individual scales. Imbalance of production and community needs for grains has caused unstable prices, while price instability made this need difficult to fulfill.

Price instability could complicate in planning of production and investment activities. Stable prices could support the maintenance of people's purchasing power [6, 7]. In the case of price instability, producers and consumers needed information of production forecasting and grain prices, allowing business people to carefully plan their business ventures [8, 9].

Production forecasting and price of grains with time-series data could be done using a statistical method derived from a multiple linear regression model [10, 11], but forecasting results have not been accurate [12, 13]. One of the statistical methods for analyzing time-series data is the Autoregressive Integrated Moving Average (ARIMA). The advantage of this method is that it only used past and present values of the dependent variable to produce forecasting [14-17]. This study analyzed the forecasting model of production and the prices of rice and corn commodities in Central Sulawesi, Indonesia.

2. LITERATURE REVIEW

2.1. Forecasting

Forecasting is the art, science to predict future events [18]. This is done by involving taking past data and placing it into the future with a mathematical model adapted to the good consideration of a manager. Forecasting is concerned with predicting what will happen in the future, based on the scientific method and is done mathematically [19]. However, forecasting activities are not solely based on scientific procedures or organized, because there are forecasting activities that use intuition (feelings) or through informal discussions in a group.

Forecasting is a study of historical data to find relationships, trends, and systematic patterns [20]. In the business world, forecasting results are able to provide an overview of the future of the company which allows management to make planning, create business opportunities, and manage investment patterns. The accuracy of the results of business forecasting will increase the chances of achieving a profitable investment [21]. The higher the accuracy achieved by forecasting, the greater the role of forecasting in the company, because the results of forecasting can provide direction for company planning, product and market planning, sales planning, production planning and finance.

Associated with company planning, the results of forecasting the economic and market environment allow company planners to direct company policies to the sectors that provide the highest profit opportunities [22]. The utilization of forecasting results in product and market planning is generally used to set company goals. The results of the product and market forecasting can be used by the company to enter new markets or to withdraw from increasingly unprofitable markets.

Forecasting is usually based on the future time horizon it covers [23]. The time horizon is divided into several categories, namely: (1) Short-term forecasting: this forecasting covers a period of up to one year but generally less than three months, is used to plan purchases, work schedule, number of labor, work assignments, and population levels; (2) Medium-term forecasting (intermediate): this forecasting includes a monthly count of up to three years, is useful for plan sales, planning and production budget, cash budgeting and analyzing various operational plans; (3) Long-term forecasting: generally for planning periods of three years or more. This forecasting is used to plan new products, capital expenditures, location or facility development, as well as research and development.

2.2. Arima Method

The Box-Jenkins or ARIMA method is a method that uses a time series basis with a mathematical model [24], with the objective that errors that occur can be as small as possible. The use of the ARIMA method requires identification of the model and estimating its parameters [25]. This method is very good for short-term forecasting. ARIMA method is a combination of Autoregressive (AR) and Moving Average (MA) models. ARIMA model shows the dependent variable which is affected by the dependent variable itself in previous periods [24]. What distinguishes the AR and MA models is the type of independent variable. The independent variable in the AR model is the previous value (lag) of the dependent variable itself, while in the MA model the independent variable is the residual value in the previous period.

An important requirement so that data can be modeled using the ARIMA method is data stationarity [26]. Stationarity is needed to make it easier to identify and draw conclusions. Time series data is said to be stationary if the data shows a constant pattern from time to time. Data that are not stationary at the mean can be overcome by doing a first or second differentiation. In accordance with differentiation to what degree the data is stationary. Meanwhile, non-stationary data on variance can be overcome by transforming it.

The Box Jenkins forecasting method is a very precise method for dealing with or overcoming the complexity of time series and other forecasting situations [27]. This complexity occurs because there are variations in the existing data patterns so that an approach is needed to predict data with this complex pattern by using several relatively good rules. In addition, this method can be used to predict historical data with conditions that are difficult to understand its effect on data technically, therefore necessary to know and understand some of the technical basics of its application.

This forecasting method is actually a very general approach to time series forecasting. The reason for developing this method is because the existing forecasting methods always assume or are limited only to certain kinds of data patterns [28]. The Box Jenkins method does not require assumptions about a fixed pattern. The Box Jenkins approach begins with assuming an experimental or tentative pattern that is adjusted to historical data so that errors can be minimized.

The Box Jenkins approach provides information explicitly to enable researchers to think about or decide whether the patterns that tentatively assumed are appropriate or true for the conditions and situations that have occurred [29]. If this has been done, the forecast can be made immediately and if it does not match the assumed pattern, the Box Jenkins approach provides further signs to identify the correct pattern. The procedures that are performed repeatedly allows the researcher to arrive at a forecasting model that provides optimism in the size of the basic pattern and minimizes the possibility of errors.

The Box Jenkins approach divides the forecasting problem into three stages based on the postulation of a common class of forecasting models. In the first stage, a certain model can be entered tentatively as a forecasting method which is very suitable for the identified situation. In the second stage, match the model to the available historical data and perform a check to determine whether the model is sufficiently correct. If not correct, the approach returns to the first stage and an alternative model is identified. If a model is sufficiently precise, it should be isolated, and the third stage is to formulate forecasts for the next several periods.

Basically, there are two models of the Box Jenkins method, namely linear models for static series and linear models for non-static series. Linear models for static series use filtering techniques for time series, namely ARMA (Autoregressive-Moving Average) model for a data set. Linear models for non-static series use ARIMA (Autoregressive Integrated Moving Average) models [30].

The real advantage of ARIMA models is that the forecasts done can be developed for very short periods. More time is spent on obtaining applicable data than time for modeling. According to Hanke et al. [31], in practice, the ARIMA model is often used.

1. Autoregressive (AR) Model:

In general, the AR process of the p^{th} order (AR (p)) can be written as follows:

$$X_t = \emptyset_0 + \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \cdots + \emptyset_p X_{t-p} + e_t \quad (1)$$

Where :
X_t = data at time t, t = 1,2,3, …, n
X_{t-1} = data at time t-i, i = 1,2,3, …, p
$\emptyset_0$ = constant value
$\emptyset_i$ = i^{th} autogressive parameter,i = 1,2,3, …, p
e_t = error value at time t

2. Moving Average (MA) Model:

In general, the MA process of the q^{th} order (MA (q)) can be written as follows:

$$X_t = \emptyset_0 + \emptyset_1 e_{t-1} + \emptyset_2 e_{t-2} + \cdots + \emptyset_q e_{t-q} + e_t \quad (2)$$

Where :
X_t = data at time t, t = 1,2,3, …, n
$\emptyset_0$ = a constant
e_t = error value at time t
e_{t-j} = error value at time t-j, j = 1,2,3, …, q
$\emptyset_j$ = j^{th} MA parameters, j = 1,2,3, …, q

3. Mixed Model or Autoregressive and Moving Average

In general, it can be expressed in the form

$$X_t = \emptyset_0 + \emptyset_1 X_{t-1} + \cdots + \emptyset_p X_{t-p} - \emptyset_1 e_{t-1} - \cdots - \emptyset_q e_{t-q} \quad (3)$$

Where :
X_t = data at time t,t = 1,2,3, …, n
$\emptyset_0$ = a constant
X_{t-i} = data at time t-i, i = 1,2,3, …, p
$\emptyset_i$ = i^{th} autogressive parameter
e_t = error value at time t
e_{t-j} = error value at time t-j, j = 1,2,3, …, q
$\emptyset_j$ = j^{th} MA parameters, j = 1,2,3, …, q

Besides being known as ARIMA, this method is also popularly known as the Box-Jenkins method, because it was developed by two American statisticians, namely G.E.P Box and G.M Jenkins in 1970. The ARIMA process can be expressed as:

ARIMA (p, d, q) (4)

Where :

p = number for autoregressive (AR)

d = number for differencing orders

q = number for moving average (MA)

3. METHOD

3.1. Location And Data Sources

This study was conducted in Central Sulawesi in January of 2020. The study used time-series data from 2015 to 2019. The variables collected were rice and corn production and rice and corn prices. Sources of data came from the Department of Industry and Trade and the Department of Food Crops and Horticulture in Central Sulawesi. Forecasting of production and prices used the ARIMA Box Jenkins Method.

3.2. Determination of the Forecasting Model of production and price of grains

Table 1 exhibits the regression equation of forecasting of production and price of grains.

Table 1. Equation of forecasting of production and price of grains in Central Sulawesi

Variable	Autoregressive Model (AR)	Moving Average Model (MA)
Rice production	$Y_{1t} = a + a_1Y_{t-1} + \ldots + a_iY_{t-I} + e_t$	$Y_{1t} = e_t - Y_1e_{t-1} - Y_1e_{t-2} - \ldots Y_ne_{t-n}$
Rice price	$Y_{2t} = a + a_1Y_{t-1} + \ldots + a_iY_{t-I} + e_t$	$Y_{2t} = e_t - Y_1e_{t-1} - Y_1e_{t-2} - \ldots Y_ne_{t-n}$
Corn production	$Y_{3t} = a + a_1Y_{t-1} + \ldots + a_iY_{t-I} + e_t$	$Y_{3t} = e_t - Y_1e_{t-1} - Y_1e_{t-2} - \ldots Y_ne_{t-n}$
Corn Price	$Y_{4t} = a + a_1Y_{t-1} + \ldots + a_iY_{t-I} + e_t$	$Y_{4t} = e_t - Y_1e_{t-1} - Y_1e_{t-2} - \ldots Y_ne_{t-n}$

Note: $a - a_i$ = AR coefficient, $Y_1 - Y_n$ = MA coefficient

The best forecasting model of production and price of grains was selected based on the adjusted R^2 value criteria, Akaike information criteria (AIC), and Schwarz information criteria (SIC). If the model met more than one of these requirements, it was chosen again based on the value of the Root Mean Square Error (RMSE) [32, 33]. The model with the smallest RMSE value was the most suitable model for forecasting. The combination of Autoregressive (p) and Moving average (q) formed the ARIMA model (p, d, q) where p was the AR order, q was the MA order, and d was the number of differences to obtain data that was stationary to the average. An important requirement for modeling data on the ARIMA time-series method was the data stationarity.

The current study processed production data and grain prices using the Eviews application version 9. The study used the best forecasting model to predict the value of production and price of grains for the period of January to December 2020.

4. RESULTS AND DISCUSSION

4.1. Stationary Test and Model

To get the best forecasting model it is necessary to do a stationary test. The production data for rice and corn, rice price and corn price carried out by the Box-Cox transformation shows that the rounded value (λ) was equal to 1.00 occurred in the second transformation so that a decision could be made that the production data of rice and corn, rice price and corn price were already stationary to variance (Figures 1a, 1b, 1c, 1d).

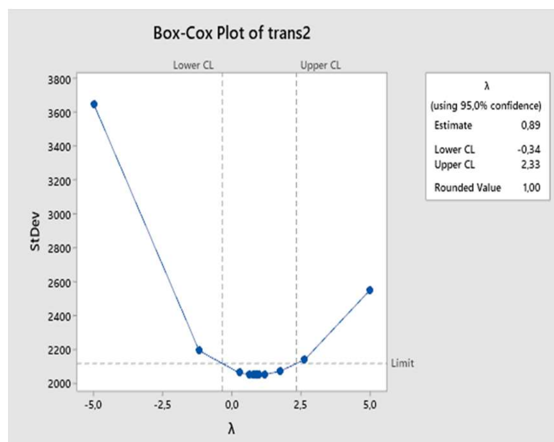

Figure 1a. Box-Cox Plot Of Rice Production Data

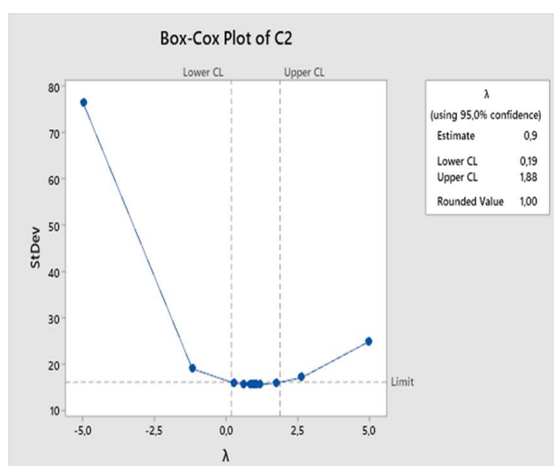

Figure 1b. Box-Cox Plot Of Corn Production Data

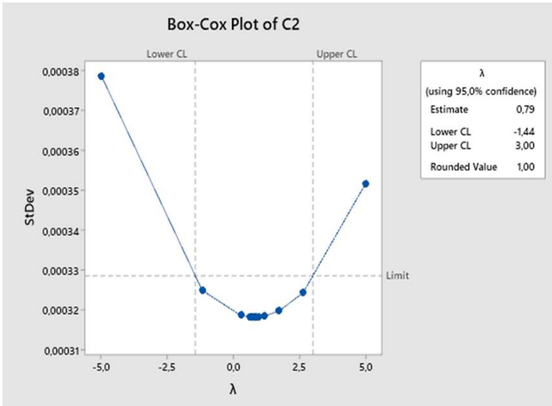

Figure 1c. Box-Cox Plot Of Rice Price Data

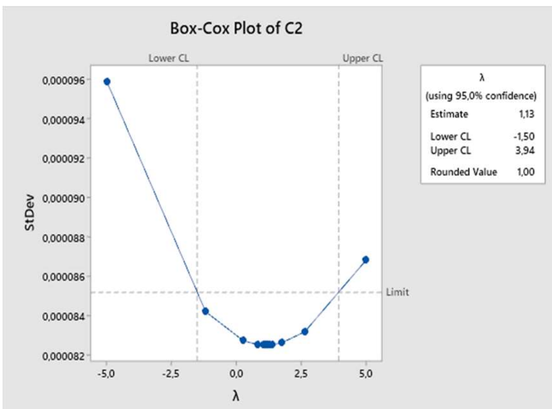

Figure 1d. Box-Cox Plot Of Corn Price Data

The ACF (Autocorrelation Function) plot of production data for rice and corn, rice price and corn price in the second transformation has also been stationary to the average (Figures 2a, 2b, 2c, 2d). This could be seen from lag 1 and lag 2 that came out of the confidence interval (cut-off).

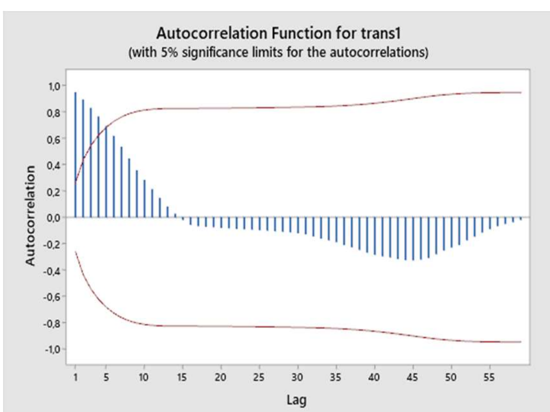

Figure 2a. ACF Of Rice Production Data

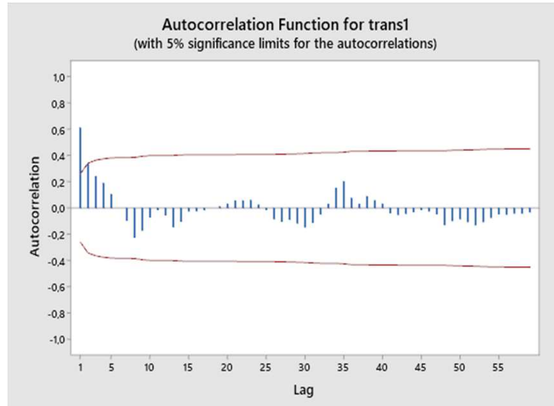

Figure 2b. ACF Of Corn Production Data

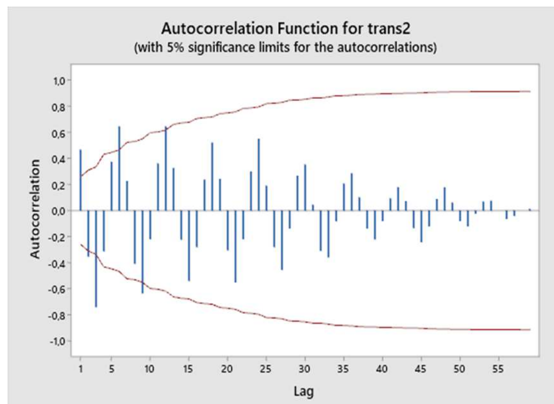

Figure 2c. ACF Of Rice Price Data

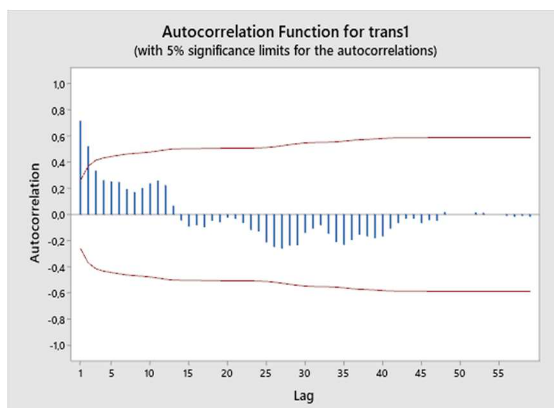

Figure 2d. ACF Of Corn Price Data

Table 2 exhibits the analysis results of the best forecasting model of production and price of rice and corn. The model can predict the production and price of rice and corn for January to December 2020.

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Table 2. The best forecasting models of production and price of rice and corn in Central Sulawesi

production and price	Variable	ARIMA Model (p, d, q)
Rice production	Y_1	(4,0,0)
Rice price	Y_2	(2,2,0)
Corn production	Y_3	(1,0,0)
Corn Price	Y_4	(2,2,0)

4.2. Rice Production Forecasting in Central Sulawesi

Table 3 lists the results of rice production forecasting.

Table 3. rice production forecasting from January to December 2020 in Central Sulawesi

Month	Rice Production Forecast (ton)
January	37,137
February	36,143
March	35,077
April	33,938
May	32,727
June	31,443
July	30,087
August	28,657
September	27,156
October	25,582
November	23,935
December	22,215

Table 3 reveals the results of the rice production forecast for 2020 with the ARIMA method, which indicated a decrease in production. This happened because of the reduced size of the rice field planting area, as well as a decrease in the productivity of cultivated land. Other factors included pest attack and disease, natural disasters (floods), and the sustainable dry season. The decrease in production would be exacerbated by the ongoing COVID-19 pandemic that has hit Central Sulawesi. The decrease in production would impact the consumption needs of the population of Central Sulawesi – needs that are increasing every year. Increasing rice production could be done by increasing cultivated land area using superior varieties that are resistant to disease pests and high productivity, at the same time using balanced fertilizers, adequate irrigation, improving planting methods, enhancing mechanization and practicing soil maintenance [34-37].

4.3. Rice Price Forecasting in Central Sulawesi

Table 4 lists the results of rice price forecasting.

Table 4. Rice price forecasting from January to December 2020 in Central Sulawesi

Month	Rice Price Forecast (IDR)
January	10,153
February	10,106
March	10,041
April	9,965
May	9,883
June	9,791
July	9,687
August	9,575
September	9,452
October	9,320
November	9,178
December	9,026

Table 4 illustrates the rice price forecasting in 2021, where the price of rice has decreased monthly in the first several months of the year. This forecast is contrary to the economic rule that dictates how if production decreases, selling price will increase. This happened because the rice stock in the Indonesian Bureau of Logistics fulfilled the consumption needs of the people of Central Sulawesi, ensuring there was no imbalance between demand and supply. Moreover, there is often government interference with the price of rice in Indonesia. This result differs from the findings of Abbasi et al. [38] in Pakistan where an increase in rice production also heightened.

4.4. Corn Production Forecasting in Central Sulawesi

Table 5 lists the results of corn production forecasting.

Table 5. Results of corn production forecasting from January to December 2020 in Central Sulawesi

Month	Corn Production Forecast (ton)
January	30,686.90
February	30,581.10
March	30,786.50
April	30,981.50
May	31,166.20
June	31,340.40
July	31,504.30
August	31,657.80
September	31,800.90

October	31,933.70
November	32,056.00
December	32,168.00

Table 5 shows that the corn production forecast increases monthly. This happened because the productivity of corn agricultural land remained relatively productive for planting corn. According to Badar et al. [35], yields of wheat, rice, and corn increase when planting techniques improve. Indeed, the tropical climate in Central Sulawesi strongly supports the growth of corn [39].

4.5. Corn Price Forecasting in Central Sulawesi

The results of Corn Price Forecasting are listed in Table 6.

Table 6. Results of corn price forecasting from January to December 2020 in Central Sulawesi

Month	Corn Price Forecast (IDR)
January	8,039.51
February	8,089.44
March	8,142.10
April	8,195.49
May	8,249.07
June	8,302.70
July	8,356.35
August	8,409.99
September	8,463.64
October	8,517.29
November	8,570.94
December	8,624.59

Table 6 shows the price of corn and how it tended to increase. This happened because the consumption and use of corn as animal feed was imbalanced with corn production. In addition, there were corn products derived from Central Sulawesi that sold outside the region for animal feed needs. Central Sulawesi needed to expand its agricultural land being used for corn, thereby balancing production and consumption so that the price of corn would be stable [40, 41].

5. CONCLUSION

The best forecasting model for grain commodities in Central Sulawesi was that of ARIMA rice production (4,0,0) with decreasing production forecast data trends, and ARIMA corn (1,0,0) with increasing production forecast data trends. The forecasting model of ARIMA rice prices (2,2,0) saw decreasing price forecast data trends and ARIMA corn prices (2,2,0) saw increasing price forecast data trends. This meeting can be a reference in making decisions, especially in making policies related to the production and price of rice and corn in Central Sulawesi. This finding could be a reference when it comes to making decisions, especially in developing policies related to the production and price of rice and corn in Central Sulawesi.

REFRENCES:

[1] Jones, J.M. Regulatory Aspects of Whole Grain and Whole Grain Foods: Definitions and Labeling, Cereal Chemistry; St. Paul, Vol. 87, No. 2, 2010, pp. 150-154.

[2] Thompson, C., Smith, D. and Cummins, S. Food banking and emergency food aid: expanding the definition of local food environments and systems, International Journal of Behavioral Nutrition and Physical Activity, Vol. 16, No. 2, 2019, pp. https://doi.org/10.1186/s12966-018-0765-2

[3] Renwick, K. and Powell, L.J. Focusing on the Literacy in Food Literacy: Practice, Community, and Food Sovereignty, Journal of Family and Consumer Sciences; Alexandria, Vol. 111, No. 1, 2019, pp 24-30.

[4] BPS Indonesia. Survei Konsumsi Bahan Pokok. Badan Pusat Statistik (BPS) Indonesia, 2015 https://sirusa.bps.go.id/index.php?r=sd/view&kd=3408&th=2015

[5] BPS. Sulawesi Tengah Dalam Angka. Badan Pusat Statistik (BPS) Provinsi Sulaesi Tengah, 2018.

[6] Ahmed, D.A. and Abdelsalam, M.A.M. Inflation Instability Impact on Interest Rate in Egypt: Augmented Fisher Hypothesis Test, Applied Economics and Finance, Vol. 5, No. 1, 2017, pp. https://doi.org/10.11114/aef.v5i1.2709

[7] Hedenstierna, G. Unstable Inflation Is Harmful and More Common Supine Than Prone. American Journal of Respiratory and Critical Care Medicine, Vol. 198, No. 2, 2018, pp.146–147.

[8] Arlt, J. and Arltova, M. Forecasting of the Annual Inflation Rate in the Unstable Economic Conditions. International Conference on Mathematics and Computers in Sciences and in Industry (MCSI), 2015, pp.231–234. https://doi.org/10.1109/MCSI.2015.34

[9] Lidiema, C. Modelling and Forecasting Inflation Rate in Kenya Using SARIMA and Holt-Winters Triple Exponential Smoothing, American Journal of Theoretical and

Applied Statistics, Vol. 6, No. 3, 2017, pp. 161. https://doi.org/10.11648/j.ajtas.20170603.15

[10] Komontree, P., Tongkumchum, P., Karntanut W. Trends in marine fish catches at Pattani Fishery Port (1999-2003). Songklanakarin Journal of Science and Technology, Vol. 28, No. 4, 2006, pp. 887-895.

[11] Chesoh, S. and Lim, A. Forecasting fish catches in the Songkhla Lake basin, ScienceAsia, Vol. 34, 2008, pp. 335-340.

[12] Aasim, Singh, S.N., Mohapatra, A. Repeated Wavelet Transform Based ARIMA Model for Very Short-term Wind Speed Forecasting, Renewable Energy, Vol. 136, 2019, pp. 758–768.

[13] Mills, T.C. ARIMA Models for Nonstationary Time Series, In Applied Time Series Analysis, 2019, pp.57–69.

[14] Khashei, M., Bijari, M., Raissi, Ardali, G.A. Hybridization of Autoregressive Integrated Moving Average (ARIMA) with Probabilistic Neural Networks (PNNs), Computers & Industrial Engineering, Vol. 63, No. 1, 2012, pp. 37–45.

[15] Naranjo, L., Plaza, F., Yanez, E., Barbieri, M.A. Sanchez F, Forecasting of jack mackerel landings (Trachurus murphyi) in central-southern Chile through neural networks, Fisheries Oceanography, Vol. 24, 2015, pp. 219-228.

[16] Yuan, C., Liu, S., Fang, Z. Comparison of China's Primary Energy Consumption Forecasting by using ARIMA (The Autoregressive Integrated Moving Average) Model and GM (1,1) Model, Energy, Vol. 100, 2016, pp. 384–390. https://doi.org/10.1016/j.energy.2016.02.001.

[17] Tarno, Maruddani, D.A.I. and Rahmawati, R. Application of ensemble arima, anfis for Constructing model of garlic price data in semarang, Journal of Theoretical and Applied Information Technology, Vol. 99, No. 1, 2021, pp. 75-82

[18] Sun, S., Wang, S. & Wei, Y. A new ensemble deep learning approach for exchange rates forecasting and trading. Advanced Engineering Informatics, 46, 2020, 101160.

[19] Woo, C.K., Zarnikau, J. and K.H.Cao, K.H. Unintended biases of an electricity demand forecast based on a double-log regression. The Electricity Journal, 33 (10), 2020, 106866.

[20] de Haan, J., Mavromatis, K. and Tan, G. Individual inflation forecasts and monetary policy announcements. Economics Letters, 197, 2020, 109602.

[21] Nwokike, C.C., Offorha, B.C., Obubu, M., Ugoala, C.B. and Ukomah, H.I. (2020). Comparing SANN and SARIMA for forecasting frequency of monthly rainfall in Umuahia. Scientific African, 10, 2020, e00621.

[22] Huh, S. and Kim, I. Growth forecast revisions over business cycles: Evidence from the Survey of Professional Forecasters. Economics Letters, 196, 2020, 109541.

[23] Yagli, G.M., Yang, D. and Srinivasana, D. Reconciling solar forecasts: Probabilistic forecasting with homoscedastic Gaussian errors on a geographical hierarchy. Solar Energy, 210, 2020, 59-67.

[24] Shadab, A., Ahmad, S. and Said, S. Spatial forecasting of solar radiation using ARIMA model. Remote Sensing Applications: Society and Environment, 20, 2020, 100427.

[25] Selvaraj, J.J., Arunachalam, V., Coronado-Franco, K.V., Romero-Orjuela, L.V. and Ramírez-Yara, Y.N. Time-series modeling of fishery landings in the Colombian Pacific Ocean using an ARIMA model. Regional Studies in Marine Science, 39, 2020, 101477.

[26] Akhter, M.F., Hassan, D. and Abbas, S. Predictive ARIMA Model for coronal index solar cyclic data. Astronomy and Computing, 32, 2020, 100403.

[27] Ho, W.T. and Yu, F.W. Predicting chiller system performance using ARIMA-regression models. Journal of Building Engineering, 33, 2020, 101871

[28] Duan, X. and Zhang, X. ARIMA modelling and forecasting of irregularly patterned COVID-19 outbreaks using Japanese and South Korean data, 2020.

[29] Fanoodi, B., Malmir, B. and Jahantigh, F.F. Reducing demand uncertainty in the platelet supply chain through artificial neural networks and ARIMA models. Computers in Biology and Medicine, 113, 2019, 103415

[30] Zhang, G.P. Time series forecasting using a hybrid arima and neural network model. Neurocomputing 50, 2003, 159–175.

[31] Hanke, John E., Reitsch, Arthur G., and Wichern, Dean W. Business Forecasting 7th (seventh) Edition. Published by Prentice Hall. 2001

[32] Hong, T., Kim, C.J., Jeong, J., Kim, J., Koo, C., Jeong, K., Lee, M. Framework for Approaching the Minimum CV (RMSE) using Energy Simulation and Optimization Tool, Energy Procedia, Vol. 88, 2016, pp. 265–270.

[33] Mentaschi, L., Besio, G., Cassola, F. and Mazzino, A. Problems in RMSE-based wave model validations, Ocean Modelling, Vol. 72, 2013, pp. 53–58.

[34] Naohisa, K., and Robertson, A.W. Ines AVM, Qian JH, DeWitt DG, Lucero A, Prediction of Rice Production in the Philippines Using Seasonal Climate Forecasts, Journal of Applied Meteorology and Climatology; Boston, Vol. 52, No. 3, 2013, pp. 552-569.

[35] Badar, N., Fatima, H., Jabbar, A., Asif, M. Major Food Crops Production And Yield Forecast In Pakistan, Pakistan J. Agric. Res., Vol. 28, No. 3, 2015, pp. 295-303.

[36] Zahra, N., Akmal, N., Naheed, S., Habib, N., Siddiqui, S., Raza, I. Trend analysis of rice area and yield in Punjab, Pakistan J. Agric. Res. Vol. 28, No. 4, 2015, pp. 439-444.

[37] Antara, M. and Effendy. Allocation optimization of farmers' resources to achieve maximum income in Parigi Moutong Regency, Asian J. Sci. Res., Vol. 11, 2018, pp. 267-275.

[38] Abbasi, S.S., Tahir, A., Raza, I., Abid, S. and Khan, M.N. Trend analysis and forecasting of wheat and rice prices in Pakistan, Pakistan J. Agric. Res., Vol. 28, No. 3, 2015, pp. 310-317.

[39] Mathieu, J.A. and Aires, F. Statistical Weather-Impact Models: An Application of Neural Networks and Mixed Effects for Corn Production over the United States, American Meteorological Society, Vol. 55, 2016, pp. 2509-2527.

[40] García-Salazar, J.A. and Skaggs, R.K. Crawford TL, World price, exchange rate and inventory impacts on the mexican corn sector: a case study of market volatility and vulnerability, Interciencia; Caracas, Vol. 37, No. 7, 2012, pp. 498-505.

[41] Dutta, A., Bouri, E., Junttila, J. and Uddin, G.S. Does corn market uncertainty impact the US ethanol prices? Global Change Biology, Bioenergy; Oxford, Vol. 10, No. 9, 2018, pp. 683-693. DOI:10.1111/gcbb.12527