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Forecasting Monthly Prices of Selected Agricultural Commodities in The Philippines Using ARIMA Model

Karen Gail Ramos, Irish Joan O. Ativo

College of Business Administration Graduate School, Polytechnic University of the Philippines, Sta. Mesa Manila, Philipines, Sta Mesa Manila, Philippines

College of Business Administration Graduate School, Polytechnic University of the Philippines, Sta. Mesa Manila, Philipines, Sta Mesa Manila, Philippines

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A B S T R A C T

Prices of commodities affected both producers and consumers thus, determining its future value is relevant for future decision-making. This study aims to guide the policymakers in creating guidelines for the benefit of the producers and consumers of agricultural commodities like sitao, eggplant, tomato, whole chicken, pork ham, and pork liempo. The researchers analyzed the data behavior of the selected commodities for the years 2013-2022 which all be observed to have an upward trend with fluctuations. These fluctuations are found to be connected to different factors such as seasonality of production, surplus of volume, pest & diseases, typhoon devastation, and importation, among others. After the analysis of price behavior, the researcher then, forecasted the price of this agricultural produce using the ARIMA technique. The data was first tested for its stationary through Augmented Dicker Fuller (ADF) Test, which resulted in the first differencing. The results of the ARIMA technique revealed that ARIMA (2,1,2), ARIMA (8,1,3), ARIMA (9,1,3), ARIMA (67,1,29), ARIMA (1,1,35) ARIMA (3,1,2), ARIMA (1,13), ARIMA (3,1,6), ARIMA (3,1,2), and ARIMA (3,2,5) for the whole chicken, pork ham, pork belly, beef brisket, chicken egg, sitao, eggplant, tomato, carrot, and cabbage respectively, are the best-fit models to forecast the next five years (2023-2027) prices of the commodities.

Keywords: ARIMA, ADF, Forecasting, Agriculture, Prices

1. Introduction

As an agricultural country, agricultural commodities play a significant role in the Philippine economy. In 2020, agricultural commodities contributed about PHP 307.63 billion, or 9.5% of the country's total export revenue with major agricultural exports such as corn, banana, pineapple, and coconut. It also contributed 10% to the GDP of the year 2022, (Philippine Statistics Authority (PSA), 2021). However, the Philippines is considered the most food-insecure among other countries in emerging Asia. The country's reliance on imported food to feed its growing population is the primary measure of this vulnerability. The total agricultural import value of the country, in 2021, was recorded to be PHP 700.73 billion whereas, in 2022, the U.S. Department of Agriculture (USDA) Foreign Agricultural Service projected that their export to the Philippines might reach up to 3.8 billion dollars.

Agricultural commodity prices have a volatile nature of the perishability and vulnerability of agricultural commodities to various factors such as natural calamities, pests and diseases, weather, and climate change. The COVID-19 pandemic did not make it easy for agricultural exports which posed a significant decrease from PHP 345.76 billion (2019) to PHP 307.63 (2020), (PSA, 2021). It was magnified as well by the ongoing Ukraine-Russia war which affected the prices of crude oil and petroleum due to logistical restrictions. These factors pushed further the inflation of agri-commodities in a very short period of time. Some major agricultural commodities prices presented drastic movement from the month of November to December such as rice (3.1% to 3.4%); fish and other seafood (6.3% to 8.3%); flour, bread, and other bakery products, pasta products, and other cereals (10.9% to 10.3%); milk, other dairy products, eggs (9.9% to 9.4%); oils and fats (19.2% to 19.8%); meat (7.4% vs. 8.6%); and vegetables (32.4% vs. 25.8%), (PSA, 2021). Analysis of the behavior of agricultural commodity prices to forecast is relevant since it can be part of the basis of possible policy decisions to respond to price fluctuations. Hence, this study provides an overview of forecasting agricultural commodity prices through the time-series ARIMA model.

1.1. Objective of the Study

The main objective of this study is to determine the price behavior of the identified top three commodities from two selected groups such as vegetables and livestock & poultry for the years 2013-2022 and to create a forecast for the next five years (2023-2027) using ARIMA model. Moreover, the study will specifically aim to:

Analyze the behavior of the prices of the following:
Vegetable commodity-

- Sitao
- Eggplant
- Tomato
- Carrot
- Cabbage

Livestock & poultry commodity-

- Beef Brisket
- Pork Ham
- Pork Liempo
- Whole Chicken
- Chicken Egg

Forecast the prices of the identified agricultural commodities for the next five years (2023-2027)

1.2. Research Paradigm

The researchers use a conceptual framework to guide forecasting agricultural produce in the Philippines, such as vegetables, and livestock & poultry. It follows a three-step process which includes the research's input, process, and output. The figure below shows the Input-Process-Output model for this research.

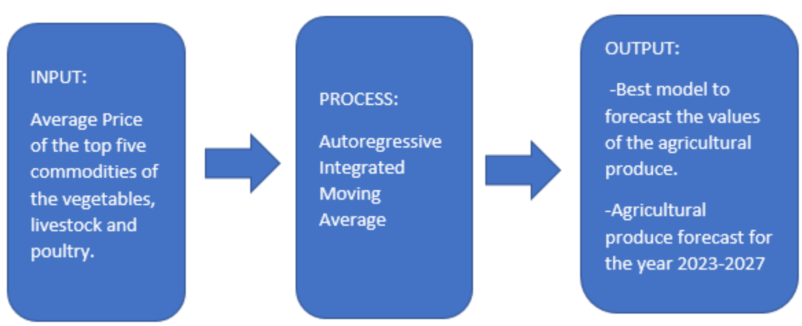


Figure 1. Research Paradigm

1.3. Conseptual Framework

The data used in this study was the monthly prices of the chosen commodities from 2013 to 2022. The study utilizes the ARIMA model to forecast the prices of the chosen commodities for the next five years (2023 to 2027).

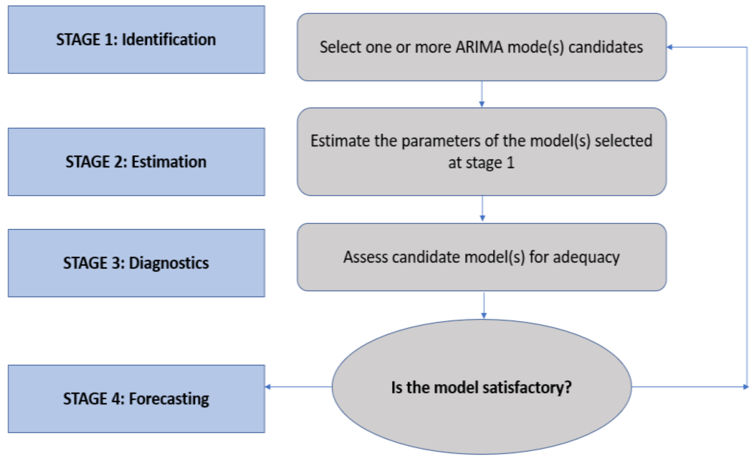


Figure 2. Conceptual Framework

1.4. Scope and Limitations

The scope of the study is the prices of the top five identified commodities of the vegetables and livestock & poultry commodities such as sitao, eggplant, tomato, carrot, cabbage, beef brisket, pork ham, pork liempo, whole chicken, and chicken egg from 2013-2022. On the other hand, the limitation of the study is it utilizes average monthly prices of commodities from selected public markets in the National Capital Region (NCR).

1.5. Related Review of Literature

Analysis of agricultural commodity prices is significant in the field of work on agriculture given its main role in the determination of production decisions of farmers, policymakers, and the government. A study by Huchet-Bourdon, M. (2011) entitled "Agricultural Commodity Price Volatility" where the price volatility of agricultural prices in 2006-2010 was identified and compared with the prices during the 1970s. It was shown that for 2006-2008, there was a sharp increase in prices of agricultural commodities compared to low levels of prices during the 1970s. However, the prices for the period of 50 years followed a similar pattern where a price hike in 1 year then a significant drop the next year for most commodities. It was also observed that surges in agricultural prices took place in the period when there was a general rise in all most commodities like crude oil and metals.

In a study by Piot-Lepetit and M'Barek (2011), various methods to analyze agricultural commodity price volatility were presented. Agricultural commodity prices were observed to be sensitive to the changes in supply and demand conditions. Agricultural commodities differ from other price-volatile commodities because of three characteristics: seasonality of production, derived nature of their demand, and price-inelastic demand and supply functions. The analysis of agricultural commodity prices was mostly presented through temporal or time series behaviors of prices.

Magnogna, R.L., and Mishra, (2020) emphasized the importance of forecasting agricultural commodity prices not only to the government but also to farmers and business enterprises venturing into agriculture, given its impact on both procedures and consumers. The availability of price information on agricultural commodities serves both private and public entities' interests given the increasing market integration and globalization.

The analysis of past and current data can predict the possible situation in the near future. In statistics, there are many ways to accurately forecast commodity prices and some researchers use the Autoregressive Integrated Moving Average (ARIMA) to forecast available data.

The study by Bhardwaj, S.P. Et Al. (2014) deals with the time series model, which is non-structural mechanical. ARIMA and GARCH were applied in the forecasting and modeling of the Gram prices. Results in ARIMA gave reasonable and acceptable forecasts; however, it did not perform well when the data series were volatile. The GARCH model is also suitable to perform forecasting Gram prices. It has a better ability to capture volatility. GARCH was preferred over ARIMA in the forecasting spot price for Gram because the values for RMSE, MAE, MAPE, SIC, AIC, and deviations are less than the results in ARIMA.

In the conducted study by Jadhav, V. et al. (2017). It demonstrated the utility of price forecasting of farm prices and validate the same for significant crops in Karnataka state in 2016. The forecast was obtained by performing ARIMA techniques. The results exhibit the power of the ARIMA technique as a tool for price forecasting. The MSE, MAPE, and Theils U values were relatively low, indicating the validity of the price forecasted through ARIMA.

In the study of Molina, I. & Delos Reyes, J., (2017), the seasonality in the monthly prices of pork in the Philippines was captured. Data was collected from the PSA website. ARIMA X-12 was used to seasonally adjust the monthly farm gate and retail prices of pork in the Philippines. The outcome showed that both price series exhibited clear upward trends and normal irregular variations. F-tests also revealed that monthly farm gate and retail prices of pork present stable seasonality and moving seasonality at a 1% probability level. Trading day and leap year effects were found to be insignificant.

The paper of Darekar, Ashwini, et Al. (2016), showed the forecasted prices of onions at the Kohlapur market in Western Maharashtra. The data was gathered from the register maintained by Kohlapur APMC. ARIMA predicted the price and revealed that there would be a price and demand increase in the future. Researchers suggest that farmers need to plan their production process in such a way that a reasonable price for the produce is also expected.

In the paper of Kaviraju, S. et al (2017), the monthly prices of maize using ARIMA were forecasted. The results indicate ARIMA(2,1,1) is the most adequate and efficient model. ARIMA (2,1,1) was established by comparing various models among Akaike Criteria, Bayesian Information Criteria, and Mean Absolute Percentage Error. The forecasted results show that there will be an increase in maize prices in the Badepalli market in the next five months.

In the study by Urrutia, J. et al. (2014), forecasting the Foreign Trade of the Philippines was emphasized to be important since it affects both local and trade investment, as well as, the price stability of commodities. The study focuses on using a specific type of ARIMA which is the Seasonal ARIMA model or SARIMA to forecast foreign trade. Another study by Urrutia, J. et al., (2018) presented the forecasting of electricity rates through the use of the ARIMA model where the best candidate ARIMA (p,d,q) was chosen.

In the study of Urrutia, J. et al. (2019), the imports and exports of the Philippines were forecasted through ARIMA and Bayesian Artificial Neural Network (BANN) techniques. The results of BANN suggested that is the most fitted model for forecasting the imports and exports in the Philippines. Upon using the Paired T-test, the p-value for both imports and exports are greater than the level of significance, which means that there is no significant difference between actual and predicted values for both imports and exports of the Philippines.

In forecasting rice production in Luzon Using Integrated Spatio-Temporal Forecasting Framework by Urrutia, J. et al. (2019). The possibility of using spatial data and temporal data in forecasting the production of rice at the same time was explored. This study indicates that if there exists a stronger spatial correlation between the target subcomponent and non-target subcomponents, the better forecasting framework is spatiotemporal since it can obtain better prediction performance.

In the study by Urrutia, J. et al. (2019) entitled "Forecasting The Gross Domestic Product of The Philippines Using Bayesian Artificial Neural Network and Autoregressive Integrated Moving Average", the best-fitting forecasting model between ARIMA and BANN in forecasting the Gross Domestic Product (GDP) of the Philippines from 1990 was determined. ARIMA (1,1,1) and BANN were compared, which resulted in BANN being the best-fitted model for forecasting the GDP of the Philippines.

2. Methodology

Data Source

The study has been illustrated with the time series data of 5 selected Vegetables, Livestock, and Poultry in the Philippines from January 2013 to December 2022. The data were gathered from the Department of Agriculture and Philippine Statistics Authority website. The last 60 observations were forecasted, used to validate the models, and not considered for building the model. The methodologies were employed to test the data's time series properties, identify and fit the models, and check the models with time series data.

Model Description

ARIMA

Autoregressive Integrated Moving Average is a statistical model for analyzing and forecasting time series data. The components of ARIMA are specified in the model as a parameter. A standard notation would be ARIMA with p, d, and q as integers substitutes for the parameter to indicate the type of ARIMA model used. Parameters can be defined as:

- p: as the lag order, it is the number of lag observations in the data.
- d: the degree of differencing is the number of times the raw observations are differenced
- q: the order of the moving average is the size of the moving average window.

Given this, the general case of ARIMA can be written as follows:

$$X_t = \alpha_1 X_{t-1} + \cdots + \alpha_p X_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q}$$

Predicted Xt = Constant + Linear combination of Lags of X) + Linear Combination of Lagged forecast errors. Provided that the time series is already different to ensure stationarity.

Implementing an ARIMA model for time series presumes that the observations are an ARIMA process. A linear regression model is established, together with the specified number and type of terms, to execute the ARIMA. The data is produced by a degree of differencing to make it stationary.

Determining the p, d & q

ARIMA models are presumed to be stationary. Implementing differencing may give rise to stationarity for various time series. The easiest way to determine d for our models is to differentiate and run ADF to check for stationarity. After determining the d we may now look at the ACF and PACF for the AR (p) and MA (q).

Augmented Dickey-Fuller (ADF)

The ADF test is a unit root test for stationary. It can be used with serial correlation. It is the most commonly used statistical test in analyzing the stationary of a series.

The ADF test is the expanded version of the Dickey-Fuller test equation to include the high-order regressive process in the model.

$$y_t = c + \beta t + \alpha y_{t-1} + \phi_1 \Delta Y_{t-1} + \phi_2 \Delta Y_{t-2} . . + \phi_p \Delta Y_{t-p} + e_t$$

The null hypothesis assumes that the presence of unit root is α=1, and the p-value should be less than the significance level (say 0.05) to reject the null hypothesis. Thereby concluding that the series is stationary.

In finding the P term or Autoregressive

We can examine the PACF plot to ascertain the lag for our AR terms. Partial autocorrelation can be visualized as the correlation between the series and the lag after excluding the input from the intermediate lags. So, PACF conveys the pure correlation between a lag and the series. That way, we will know whether that lag is needed in the AR term.

In finding q or the moving average

Similar to how p was determined, we will now examine the ACF to determine the q terms to be considered for MA. The ACF will tell how many MA terms are required to remove the autocorrelation in the stationary series.

3. Results and Discussion

Livestock & Poultry

The data shows an upward trend in the average monthly price of Poultry and Livestock commodities from 2013-2022. There was a noticeable spike increase in pork in the second quarter of 2020 caused by dread hog disease and the impact of the Covid-19 pandemic. In the last quarter of 2021, there is a decrease in trend emerged due to the importation of frozen meats and the increase in supply due to the OneDA Family" twin program of hog repopulation or INSPIRE and "Bantay ASF sa Barangay" or BABay ASF" to revitalize the country's swine industry fully. The price for poultry is volatile; however, the decrease in trend in 2020 is noticeable. The low demand caused this decrease due to bird flu, first detected in Nueva Ecija. However, it also increased during the first quarter of 2021 due to the increase in the poultry's price, which created a high demand for poultry as consumers substituted it for pork. In 2022 there is an evident increase in price for all commodities due to the Ukraine and Russia war which led to oil price hikes that affected the logistic cost that pushed the price of these commodities. Another factor is that the imports also increased in cost due to the weakening of the peso against the dollar.

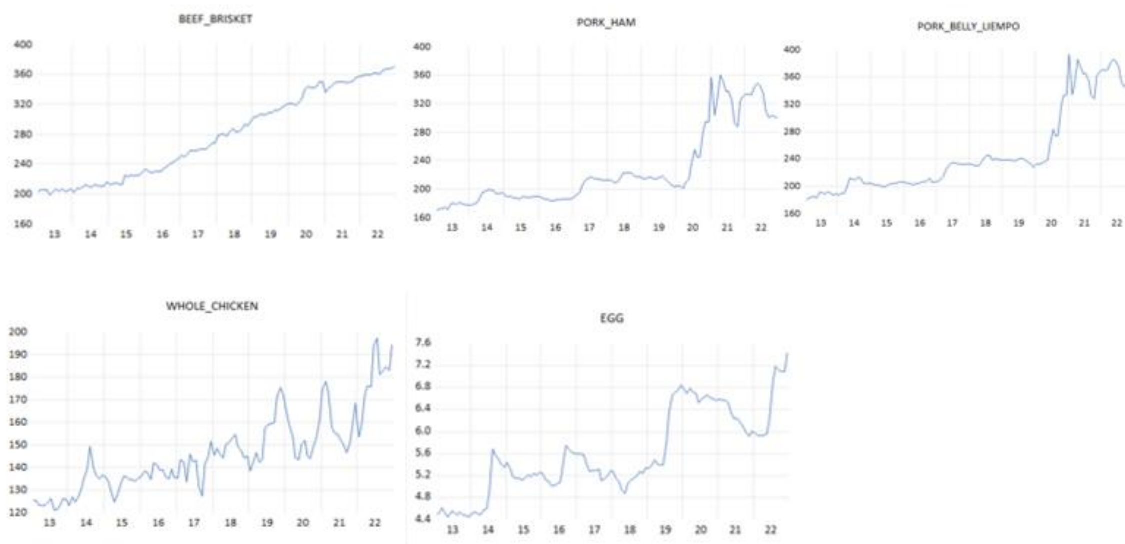


Figure 3. Graph of the average monthly price of the commodity (2013-2022)
a) Beef Brisket; b) Pork Ham; c) Pork Belly; d) Whole Chicken; e) Chicken Egg)

The chosen commodity for livestock and poultry was forecasted using the ARIMA. The ARIMA is a model used to forecast based on historical time-stamped data. The model needs three parameters; the order of the autoregressive (AR) process or p, the difference d, and the order of the moving average (MA) process or the q. ADF Test is performed to test the stationarity of the data. After the first test, it shows that there exists a unit root that needs first differencing. Therefore first differencing was applied to the chosen commodities for livestock and poultry. Performing the same test in the first difference data shows that the p-value is less than 0.05, which satisfies the time series' stationarity. This means that mean, variance, and autocorrelation are all constant over time. In the section before, it was mentioned that all of the commodities underwent a first differencing for them to be stationary. Then the second parameter or d of all the commodities is equal to 1. The sample autocorrelation function (ACF) and the partial autocorrelation function (PACF) are plotted in every commodity to provide information about AR and MA order.

ARIMA Model Estimation

Table1- ARIMA Estimation of Whole Chicken

CRITERIA	ARIMA (2,1,2)	ARIMA (17,1,17)	ARIMA (11,1,11)	BEST MODEL
AR P-Value	0.0065	0.8991	0.5439	**A**
MA P-Value	0.0000	0.4868	0.1672	**A**
SIGMASQ	31.40227	31.70931	31.99640	**A**
Log likelihood	-374.1423	-375.1842	-375.4633	**A**
Akaike (AIC)	6.355333	6.372844	6.377535	**A**
Schwarz (SC)	6.448749	6.466260	6.470951	**A**
Hannan-Quinn	6.393266	6.410777	6.415468	**A**

Table 2 - ARIMA Estimation of Pork Belly

CRITERIA	ARIMA (9,1,3)	ARIMA (8,1,8)	ARIMA (9,1,8)	BEST MODEL
AR P-Value	0.0031	0.8418	0.0090	A
MA P-Value	0.0003	0.5618	0.0080	A
SIGMASQ	114.7757	121.2521	117.1155	A
Log likelihood	-451.3592	-454.5122	-452.6760	A
Akaike (AIC)	7.653095	7.706087	7.675227	A
Schwarz (SC)	7.746511	7.799503	7.768643	A
Hannan-Quinn	7.691029	7.744020	7.713160	A

Table 3 - ARIMA Estimation of Pork Ham

CRITERIA	ARIMA (3,1,3)	ARIMA (8,1,3)	ARIMA (12,1,3)	BEST MODEL
AR P-Value	0.1128	0.0009	0.2164	B
MA P-Value	0.5850	0.0014	0.0001	B
SIGMASQ	118.7330	115.3551	118.5361	B
Log likelihood	-453.1868	-451.6071	-453.1883	B
Akaike (AIC)	7.683811	7.657262	7.683837	B
Schwarz (SC)	7.777227	7.750678	7.777253	B
Hannan-Quinn	7.721744	7.695195	7.721771	B

Table 4 - ARIMA Estimation of Beef Brisket

CRITERIA	ARIMA(67,1,29)	ARIMA(67,1,18)	ARIMA(18,1,29)	BEST MODEL
AR P-Value	0.0000	0.0000	0.1692	A
MA P-Value	0.0242	0.0913	0.0391	A
SIGMASQ	7.741005	8.424598	10.10956	A
Log likelihood	-301.7939	-304.4158	-307.9800	A
Akaike (AIC)	5.139394	5.183459	5.243362	A
Schwarz (SC)	5.232810	5.276875	5.336778	A
Hannan-Quinn	5.177327	5.221392	5.281295	A

Table 5- ARIMA Estimation of Chicken Egg

CRITERIA	ARIMA(1,1,1)	ARIMA(1,1,35)	ARIMA(1,1,36)	BEST MODEL
AR P-Value	0.7492	0.0000	0.0000	C
MA P-Value	0.1118	0.0001	0.0000	C
SIGMASQ	0.018861	0.017435	0.016538	C
Log likelihood	67.28634	69.66200	71.50407	B
Akaike (AIC)	-1.063636	-1.103563	-1.134522	B
Schwarz (SC)	-0.970220	-1.010147	-1.041106	B
Hannan-Quinn	-1.025703	-1.065630	-1.096589	B

After evaluating the ARIMA candidates these models are selected ARIMA (2,1,2) for a whole chicken, ARIMA (8,1,3) for pork ham, ARIMA(9,1,3) for pork belly, ARIMA(1,1,35) for chicken egg and ARIMA(67,1,29) for beef brisket.

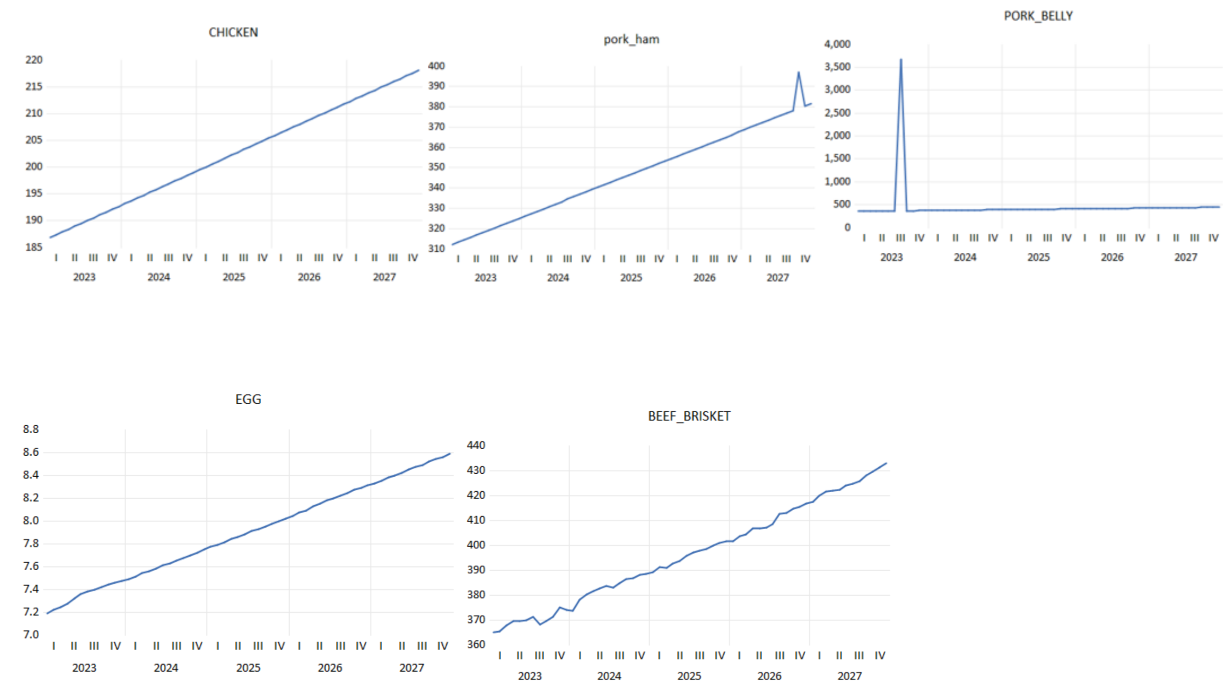
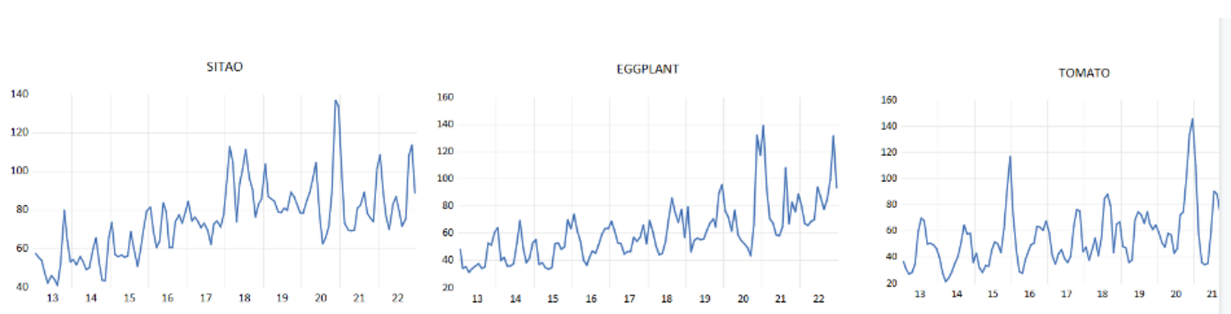


Figure 4- Forecasted Prices for a) Whole Chicken; b) Pork Ham; c) Pork belly; d) Chicken Egg; e) Beef Brisket

In figure 4, the graphs of the forecasted prices presented an upward trend. However, there are spikes in 2027 and the beginning of 2021. The spikes may result from future events that would affect the supply and production of the swine produce.

Vegetables

The study selected three commodities from the vegetable commodity group such as sitao, eggplant, and tomato, for the years 2013-2022. The data shows an upward trend in the commodity prices of sitao, eggplant, and tomato. The data of the three vegetables exhibited a similar and simple pattern of increase and decrease in prices which can be attributed to the peak and lean seasons of production. However, it can be observed in the graphs the significant spikes and sharp drops in the prices of vegetables.



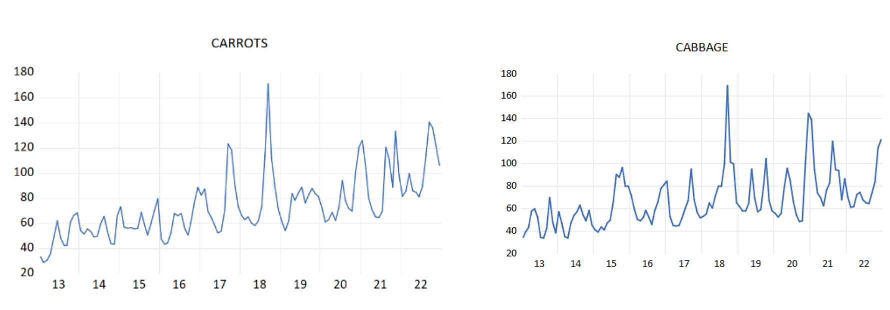


Figure 5. - Graph of the average monthly price of the commodity (2013-2022)
a) Sitao; b) Eggplant; c)Tomato; d)Carrot; e)Cabbage

In 2018, there is a significant decrease in the price of tomatoes due to oversupply during the 3rd quarter of the year. The farmers are even forced to throw away their produce since traders were not accepting their harvest. While significant spikes were due to various incidents in the agriculture sector. In early 2021, the Taal volcano erupted which resulted in damage of almost half a billion pesos worth of vegetables (lowland and highland). The Department of Agriculture along with the Local Government Units (LGUs) of the province of Batangas supported the farmers through 21.7 million worth of interventions for both crops and livestock industries, (Department of Agriculture, 2018). Another significant spike happened in the last quarter of 2020 when prices of vegetables soared due to the seasonality of produce and the two typhoons (Rolly and Ulysses). These typhoons devastated the regions of Cordillera, Ilocos, Cagayan Valley, Central Luzon, Calabarzon, and Bicol region which are known to be the main source of both lowland and highland vegetables in the country.

ARIMA Model Estimation

The data of the sitao, eggplant, and tomato was forecasted using the best ARIMA candidate for each selected vegetable, the prices from 2023-2027. First, the data was tested for its stationarity through ADF Test. The unit root did not exist after the first differencing which was applied to the chosen vegetable commodities. The test resulted in p-values less than 0.05 for all three commodities which meant that mean, variance, and autocorrelation are all constant over time.

Table 6- ARIMA Estimation of Sitao

CRITERIA	ARIMA(2,1,3)	ARIMA(3,1,2)	ARIMA(3,1,1)	BEST MODEL
AR P-Value	0.0000	0.0000	0.0039	**B**
MA P-Value	0.0000	0.0000	0.0056	**B**
SIGMASQ	0.0000	0.0000	0.0000	**B**
Log likelihood	-446.3355	-441.6204	-457.8360	**B**
Akaike (AIC)	7.568664	7.48419	7.761950	**B**
Schwarz (SC)	7.662079	7.582835	7.855366	**B**
Hannan-Quinn	7.606597	7.527352	7.799883	**B**

Table 7 - ARIMA Estimation of Eggplant

CRITERIA	ARIMA(1,1,3)	ARIMA(3,1,6)	ARIMA(6,1,10)	BEST MODEL
AR P-Value	0.0027	0.0042	0.0090	**A**
MA P-Value	0.0001	0.0266	0.0267	**A**
SIGMASQ	0.0000	0.0000	0.0000	**A**
Log likelihood	-482.1508	-484.7635	-486.4030	**A**
Akaike (AIC)	8.170602	8.214512	8.242066	**A**
Schwarz (SC)	8.264018	8.307928	8.335482	**A**
Hannan-Quinn	8.208535	8.252445	8.280000	**A**

Table 8 - ARIMA Estimation of Tomato

CRITERIA	ARIMA(4,1,2)	ARIMA(36,1,1)	ARIMA(3,1,6)	BEST MODEL
AR P-Value	0.0034	0.0054	0.0000	**C**
MA P-Value	0.0000	0.0000	0.0000	**C**
SIGMASQ	0.0000	0.0000	0.0000	**C**
Log likelihood	-485.1152	-483.1804	-481.2810	**C**
Akaike (AIC)	8.220423	8.187906	8.155983	**C**
Schwarz (SC)	8.313839	8.281322	8.249399	**C**
Hannan-Quinn	8.258357	8.225839	8.193916	**C**

Table 9 - ARIMA Estimation of Carrot

CRITERIA	ARIMA(2,1,4)	ARIMA(3,1,2)	ARIMA(4,1,2)	BEST MODEL
AR P-Value	0.0000	0.0001	0.0136	**B**
MA P-Value	0.0001	0.0000	0.0000	**B**
SIGMASQ	0.0000	0.0000	0.0000	**B**
Log likelihood	-492.6657	-490.3145	-492.6966	**B**
Akaike (AIC)	8.347323	8.307807	8.347843	**B**
Schwarz (SC)	8.440739	8.401223	8.441258	**B**
Hannan-Quinn	8.385257	8.345740	8.385776	**B**

Table 10. ARIMA Estimation of Cabbage

CRITERIA	ARIMA(3,2,2)	ARIMA(3,2,5)	ARIMA(4,1,2)	BEST MODEL
AR P-Value	0.0001	0.0050	0.0005	**B**
MA P-Value	0.0143	0.0356	0.3682	**B**
SIGMASQ	0.0000	0.0000	0.0000	**B**
Log likelihood	-504.7946	-504.7724	-505.8871	**B**
Akaike (AIC)	8.551170	8.550796	8.569531	**B**
Schwarz (SC)	8.644586	8.644212	8.662947	**B**
Hannan-Quinn	8.589103	8.588729	8.607464	**B**

Then, the ARIMA was tested where the AR and MA were analyzed by plotting the sample autocorrelation function (ACF) and the partial autocorrelation function (PACF) in every selected commodity. It was observed that the best candidates of ARIMA were ARIMA (3,1,2), ARIMA (1,13), and ARIMA (3,1,6), ARIMA (3,2,1), and ARIMA (3,2,5) for sitao, eggplant, tomato, carrot, and cabbage, respectively. As shown above in tables 4, 5, and 6.

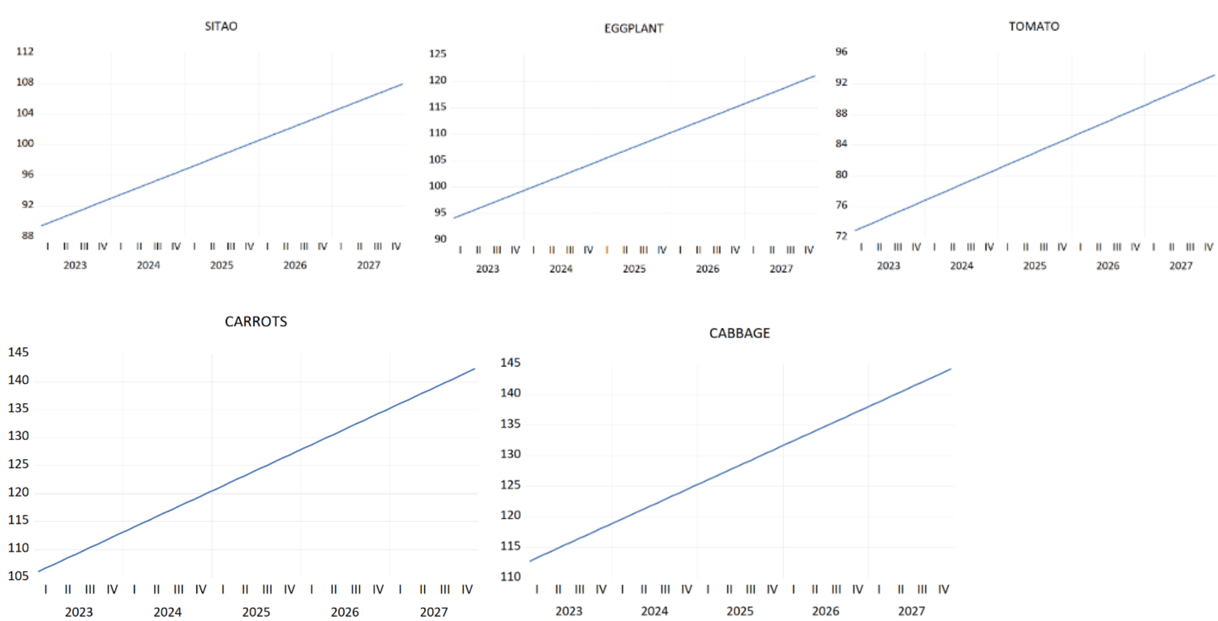


Figure 6.Forecasted Prices for a) Sitao; b) Eggplant; c) Tomato; d)Carrot; e)Cabbage

In figure 6, the forecasted prices' graphs presented an upward trend without fluctuations which varied greatly from the baseline data of these commodities.

4. Conclusions and Recommendations

In conclusion, the ARIMA model applied for forecasting Agricultural produce prices, gave reasonable and acceptable forecasts. But, it could have performed better when the data series were not volatile. The behavior prices of all selected agricultural commodities presented the same upward trend with significant spikes and sharp downs. These fluctuations are represented by various factors such as seasonality of production, damage from typhoons and other natural calamities, pest infestation, importation, smuggling issues, and economic disruptions, among others. Additionally, it can be concluded that the forecasted prices of the selected commodities presented an upward trend similar to the baseline data of 2013-2022 based on results generated from the best candidate ARIMA. However, the forecasted prices also presented a smooth trend with minimal fluctuations which contradicts the agricultural commodity prices behavior of having a rapid response to changes in supply and demand functions.

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