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Forecasting the Monthly Retail Prices of Agri-Food Condiments in the Philippines Using Autoregressive Moving Average

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***Abstract*: In this study, the aim was to identify the most suitable statistical models for forecasting the prices of Agricultural Condiments in the Philippines, which include native garlic, imported garlic, red creole onion, white onion, native onion, and ginger. An analysis of price data from 2018 to 2022 revealed no discernible upward or downward trend, indicating limited predictive value for future prices. Subsequently, employing the ARMA technique, it was determined that ARMA (11), ARMA (1,2), ARMA (1,1), ARMA (1,1), ARMA (1,24), and ARMA (1,1) are the best-fit models for forecasting prices of native garlic, imported garlic, red creole onion, white onion, native onion, and ginger, respectively, for the upcoming three years (2023-2025) in the Philippines.**

***Keywords*: agricultural-condiments, ARMA, garlic, ginger, onion, prices.**

1. Introduction

The accretion of crop prices serves as valuable information for farmers in determining the optimal time to sell their produce, aiming to maximize their benefits. Simultaneously, it aids the government in effectively managing post-harvest storage and stabilizing price fluctuations throughout the year. However, the supply of harvested crops often falls short of meeting the year's demands, primarily due to insufficient government funding for agriculture, which has led to recent increases in onion prices in 2023 (Prohit et al., 2021). As noted by Ranjit et al., timely and accurate price forecasts empower farmers to explore alternative nearby markets for their produce, ensuring they receive favorable prices. Various factors influence price fluctuations, including crop production timing, weather conditions, and supply and manpower shortages. The demand for agricultural food condiments remains consistently high, as they are essential commodities for people's daily lives. Monthly variations in agricultural crop supply and demand directly impact prices. Any imbalance in supply and demand leads to limited availability and, consequently, higher prices.

According to Business Standard (2023), onions, the second most consumed vegetable globally after tomatoes, play a crucial role in various cuisines worldwide. With an annual production of approximately 106 million metric tons, onions contribute significantly to the agri-food condiment industry alongside other staples like carrots, turnips, chilies, peppers, and garlic combined. The Philippines must regularly assess and report on the changing factors affecting agri-food condiments, as they are integral to cooking and other essential uses. The scarcity of natural resources, such as water and energy, has far-reaching implications for global governance, potentially leading to conflicts and cooperation among nations. Debates surrounding resource scarcity and its impact on international relations have persisted for decades, with agri-food condiments being one of the natural resources distributed across various countries. Any disruption in food supply can have dire consequences on global needs (Balakrishnan, 2023).

Furthermore, the Philippines' susceptibility to tropical cyclones, primarily attributed to its geographical location, leads to heavy rains, flooding, and substantial damage to both human life and property. This has a profound impact on crop production, particularly agricultural condiments. Analyzing the behavior of agricultural food prices and forecasting them is crucial, as it can inform policy decisions to address price fluctuations effectively. Therefore, this study aims to provide an overview of forecasting agricultural food retail prices using the time-series ARMA model.

A. *Objective of the Study*

The study aims to determine the most fitted statistical model in forecasting the price value of Agricultural Condiments in the Philippines. Furthermore, the study intent to forecast the value of the Agricultural Values from year 2023 to 2025.

B. *Conceptual Framework*

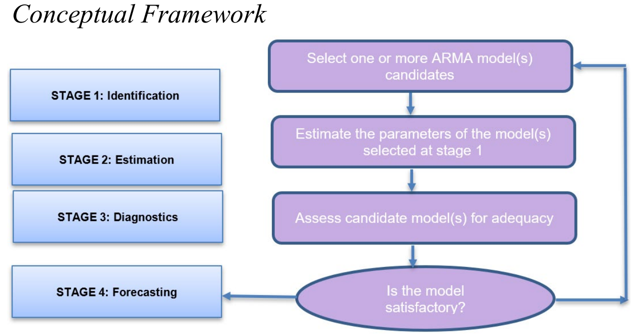

Fig. 1. Conceptual framework

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The data used in this study was the monthly prices of the chosen commodities in the Agri-Food condiments category from 2018 to 2022. The study utilizes the ARMA model to forecast the prices of the chosen Agri-Food condiments for the next three years.

C. Statement of the Problem

In order to meet the objective of the study, the following questions need to be answered by the researchers:

1. What is the trend of the graph of agricultural condiments in the Philippines?
2. What will be the statistical model of the agricultural condiments in the Philippines that can be formulated using ARMA?
3. What is the forecasted value of the agricultural condiments from January 2023 to December 2025?

D. Scope and Limitation

This study is focused on the retail price of the Agri-Food condiments such as bell pepper, imported garlic, native garlic, onion red creole, onion white, native onion, and ginger. In addition, this research is centred only on determining the forecasted retail price of those mentioned Agri-Food condiments in the Philippines.

2. Review of Related Literature

The Philippines heavily relies on its agricultural sector as a primary source of income, subject to fluctuations influenced by various factors. Christelle Jane Alto conducted a study titled "Time Series Analysis of the Price of Selected High-Value Vegetable Crops in the Philippines, 1990-2014." The objective was to examine the price variations of key crops, specifically onions and garlic, in the Philippines from 1990 to 2014. Secondary data from the Bureau of Agricultural Statistics (BAS) were collected, encompassing monthly and yearly prices, production, and harvested areas of onions and garlic at farmgate, wholesale, and retail levels. Trend analysis was utilized to ascertain the overall behavior of prices, production, and harvested areas for these crops over time. The results indicated fluctuating but generally increasing trends in onion production and harvested areas from 1990 to 2013, with annual growth rates of 2.32% and 2.60%, respectively.

The study highlighted changes in Philippine trade policies related to garlic, onions, and potatoes. During the pre-GATT period, the policies were restrictive, employing quantitative restrictions on these commodities. However, as the Philippines joined GATT-WHO in the mid-1990s, trade policies gradually liberalized. This shift resulted in positive effects on the consumption of onions, garlic, and potatoes, along with reductions in real farm and wholesale prices (except for onions). Additionally, trade liberalization led to increased volume and value of garlic and onion exports. The study also assessed price competitiveness, indicating that locally produced potatoes could compete efficiently with imports, while garlic and onions were less competitive as import substitutes.

Another study by Malayabasan (2002) estimated the own price elasticity of demand for onions in the Philippines. It utilized various factors, such as weekly consumption and retail onion prices, prices of complementary goods like garlic, source of onions, region, household size, barangay classification, socio-economic classification, total household income per week, and educational attainment of the household head. Multiple regression analysis was employed to determine the factors affecting household demand for onions, with the semi-log functional form being the most appropriate.

Valipour, Banihabib, and Behbahani (2012) aimed to forecast the inflow of the Dez dam reservoir using ARMA and ARIMA models with different parameters. Their findings suggested that the ARIMA model outperformed the ARMA model in forecasting reservoir inflow from 12 months prior, with lower error.

Balcilar and Bekun (2020) explored the spillovers between price inflation and agricultural commodity prices in Nigeria. They found a high interconnectedness among selected agricultural commodity prices and inflation, with various commodities being net receivers or givers. The study revealed a negative net spillover for price inflation, indicating a net positive spillover from commodity prices to inflation. These findings have important policy implications, emphasizing the need to manage agricultural markets to ensure price stability.

Jadhav and Reddy (2017) focused on using univariate ARIMA techniques to forecast farm prices for major crops in Karnataka, including Paddy, Ragi, and Maize for the year 2016. They found that ARIMA models were effective in price forecasting, producing relatively low values for MSE, MAPE, and Theils U coefficient criteria.

Swarup and Kushwaha (2022) estimated and forecasted the price volatility of onions in Indian wholesale markets. Their study indicated that deep learning-based LSTM models outperformed traditional models in terms of forecasting accuracy, with an accuracy rate exceeding 70% in most cases. This research has significant implications for policymakers and food supply chain stakeholders in managing market risks associated with price fluctuations.

Wang et al. (2022) proposed a combined LSTM and GARCH-family model to predict garlic prices accurately, addressing the frequent and sharp fluctuations in garlic prices. Their findings highlighted that the combined model outperformed separate models, emphasizing the potential of advanced statistical techniques in improving agricultural commodity market forecasting.

Lastly, Jinling et al. (2020) introduced a price forecasting model for ginger using a combination of Prophet and Support Vector Machine (SVM) algorithms. Their results demonstrated higher prediction accuracy and better performance compared to using either algorithm alone, with an RMSE of 0.39. This research underscores the potential of combining advanced algorithms to enhance agricultural product price prediction.

3. Methodology

A. Data Source

In this research, we indicate a time series of data from January 2018 to December 2022 for seven different condiments in the Philippines. It contains bell pepper, imported garlic, native garlic, onion red creole, onion white, native onion, and garlic. The information was obtained from the Philippine Statistics Authority's website. The total number of observations made from January 2018 to December 2022 was 60. Using Autoregressive moving average (ARMA) models, the methodologies were used to test, identify, and fit the best model or candidate for forecasting.

B. Model Description

An ARMA model, or Autoregressive Moving Average model, is used to describe weakly stationary stochastic time series in terms of two polynomials. The first of these polynomials is for auto regression, the second for the moving average.

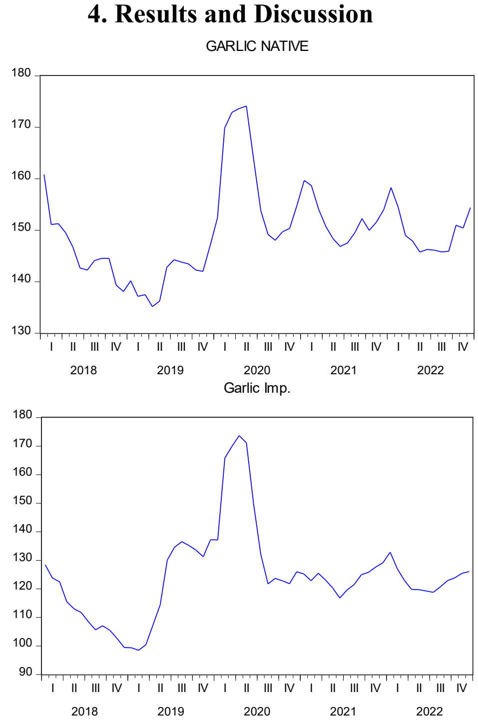
Often this model is referred to as the ARMA (p,q) model; where:

- p is the order of the autoregressive polynomial,
- q is the order of the moving average polynomial.

$$X_t = c + \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}.$$

Where:
φ = the autoregressive model’s parameters,
θ = the moving average model’s parameters.
c = a constant,
Σ = summation notation,
ε = error terms (white noise)

4. Results and Discussion



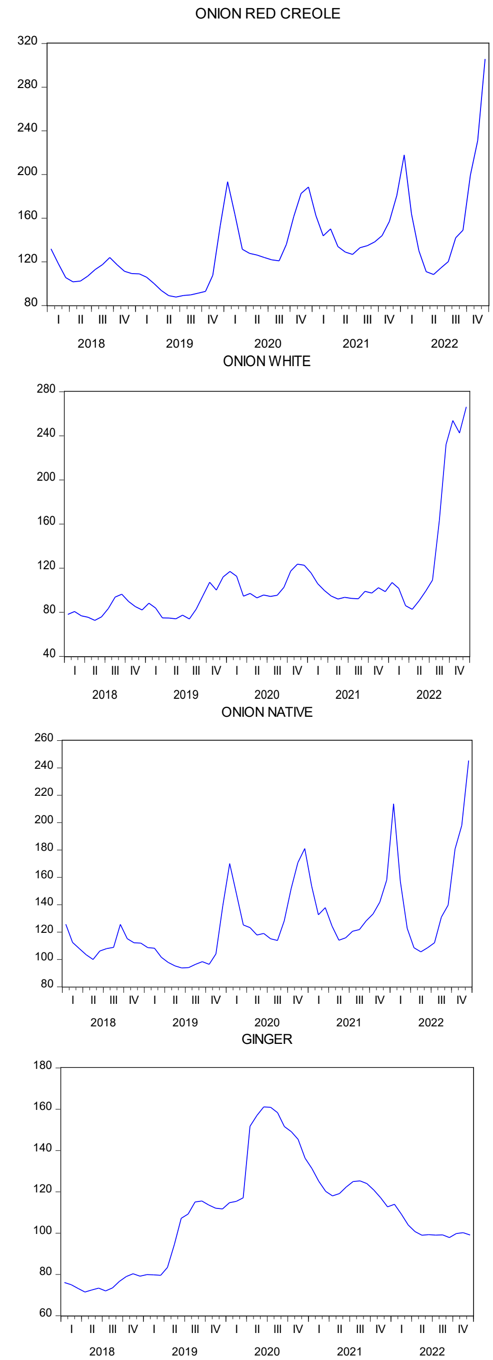


Fig. 2. Trends in agricultural condiments

The data analysis reveals notable trends in the prices of various agricultural commodities in the Philippines. For both native and imported garlic, there is a general upward trend in average monthly prices, with a notable price decrease towards the end of 2019. Subsequently, a significant price surge is observed in 2020, coinciding with the onset of the COVID-19 pandemic. As the situation gradually stabilizes, prices are returning to more typical levels.

In the case of red creole onions, white onions, and native onions in the Philippines, a distinct pattern emerges from 2018 to 2022. Prices of these commodities consistently increase every third quarter of the year, corresponding to the Christmas season, and subsequently decrease once the season concludes.

Notably, the highest onion prices were recorded in 2022, primarily due to adverse weather conditions in Cagayan Valley, a major onion-producing region in the country. The inclement weather resulted in significant damage to onion and other root crop production, leading to price spikes.

Furthermore, the data indicates a decreasing trend in the average monthly price of ginger. However, as the pandemic hit the Philippines towards the end of 2019, ginger prices began to rise. The study's findings regarding the potential therapeutic benefits of ginger against COVID-19 may have contributed to its price increase. The price surge is particularly evident from early 2020 to the beginning of 2021. Nevertheless, as the country returns to a semblance of normalcy and other cough remedies become more accessible and widely available, the demand for ginger gradually declines, leading to a decrease in its price. These trends reflect the dynamic nature of agricultural commodity prices influenced by various factors, including seasonal patterns and external events such as the COVID-19 pandemic.

A. Statistical Model using ARMA

The selected candidate will employ the ARMA model for forecasting. This model involves determining the values of p (order of the autoregressive polynomial) and q (order of the moving average polynomial). After careful analysis, it is evident that the ARMA(1,1) configuration is the most suitable choice. This decision is based on the consideration that it has the fewest parameters among the candidate models, making it a more parsimonious and practical option for forecasting within this commodity context.

The selected candidate will utilize the ARMA model for forecasting, involving the determination of p (order of the autoregressive polynomial) and q (order of the moving average polynomial). In the context of this commodity, it is evident that the ARMA(1,2) configuration is the most appropriate choice. This selection is based on the consideration that it has the fewest parameters among the candidate models, making it a more efficient and practical option for forecasting within this specific commodity context.

The chosen candidate will conduct forecasting using the ARMA model. This model involves determining p (the order of the autoregressive polynomial) and q (the order of the moving average polynomial). Within the context of this commodity, it's evident that ARMA(1,1) stands out as the most suitable choice, primarily due to its simplicity as it involves the fewest parameters among the candidate models. This makes ARMA(1,1) a practical and efficient option for forecasting in this specific commodity context.

The selected candidate will employ the ARMA model for forecasting. Within this model, the determination of p (order of the autoregressive polynomial) and q (order of the moving average polynomial) is crucial. In the context of this specific commodity, it becomes evident that the ARMA(1,1) configuration stands out as the most appropriate choice. This preference is based on the fact that ARMA(1,1) involves the fewest parameters among the candidate models, making it a practical and efficient option for conducting forecasts in this commodity context.

Table 1
Garlic native

ARMA Models	**Akaike**	**Schwartz**	**Hannan-Quinn**	**R^2**	**Adjusted R^2**
ARMA (1,1)	5.610442	5.750065	5.665056	0.816844	0.807033
ARMA (1,2)	5.743969	5.883592	5.798584	0.790087	0.778842
ARMA (1,3)	5.796424	5.936047	5.851038	0.777630	0.765717
ARMA (1,4)	5.732051	5.871674	5.786665	0.792032	0.780891
ARMA (1,5)	5.709907	5.849530	5.764521	0.797351	0.786495

Table 2
Garlic imported

ARMA Models	**Akaike**	**Schwartz**	**Hannan-Quinn**	**R^2**	**Adjusted R^2**
ARMA (1,1)	6.512696	6.652319	6.567310	0.869543	0.862555
ARMA (1,2)	6.485807	6.625430	6.543421	0.874066	0.867319
ARMA (1,4)	6.590510	6.730133	6.645124	0.858703	0.851133
ARMA (1,13)	6.587318	6.726941	6.641932	0.860827	0.853371
ARMA (1,14)	6.521819	6.661442	6.576433	0.871600	0.864722

Table 3
Onion red creole

ARMA Models	**Akaike**	**Schwartz**	**Hannan-Quinn**	**R^2**	**Adjusted R^2**
ARMA (1,1)	8.868061	9.007684	8.922676	0.771263	0.759009
ARMA (1,2)	9.053165	9.192788	9.107779	0.723268	0.708443
ARMA (1,10)	9.052651	9.192274	9.107265	0.724987	0.710254
ARMA (1,11)	8.812046	8.951669	8.866660	0.841549	0.833061
ARMA (1,12)	9.053163	9.192786	9.107777	0.723739	0.708939

Table 4
Onion white

ARMA Models	**Akaike**	**Schwartz**	**Hannan-Quinn**	**R^2**	**Adjusted R^2**
ARMA (1,1)	7.953976	8.093599	8.008590	0.920862	0.916622
ARMA (1,2)	8.264742	8.404364	8.319356	0.890677	0.884821
ARMA (1,3)	8.251850	8.391473	8.306464	0.892302	0.886533
ARMA (3,1)	9.098694	9.238317	9.153309	0.751804	0.738508
ARMA (3,2)	9.456899	9.596522	9.511513	0.636067	0.616571

Table 5
Onion native

ARMA Models	Akaike	Schwartz	Hannan-Quinn	R^2	Adjusted R^2
ARMA (1,1)	8.676265	8.815888	8.730879	0.680861	0.663764
ARMA (1,10)	8.744670	8.884293	8.799284	0.660311	0.642113
ARMA (1,11)	8.556194	8.695816	8.610808	0.746363	0.732775
ARMA (1,13)	8.729575	8.869198	8.784189	0.668972	0.651238
ARMA (1,24)	8.479588	8.619211	8.534202	0.839807	0.831225

Table 6
Ginger

ARMA Models	Akaike	Schwartz	Hannan-Quinn	R^2	Adjusted R^2
ARMA (1,1)	6.405929	6.545552	0.953551	0.953551	0.951062
ARMA (1,2)	6.459659	6.599282	6.514273	0.950966	0.948339
ARMA (1,3)	6.498422	6.638045	6.553036	0.948969	0.946236
ARMA (1,4)	6.528685	6.668307	6.583299	0.947255	0.944429
ARMA (1,5)	6.516136	6.655759	6.570750	0.947939	0.945150

Table 7
Forecasted value of agri-food condiments from the year 2023 to 2025

Year/Month	Garlic Native	Garlic Imported	Onion Red Creole	Onion White	Onion Native	Ginger
Jan. 2023	153.74	125.99	245.37	280.457	218.60	98.82
Feb. 2023	154.06	125.94	218.62	277.28	196.37	98.85
Mar. 2023	153.58	125.86	196.50	274.17	194.85	98.87
Apr. 2023	153.18	125.81	188.06	271.14	180.76	98.90
May 2023	152.84	125.75	180.36	268.19	169.24	98.92
Jun. 2023	152.55	125.71	184.05	265.30	166.15	98.95
Jul. 2023	152.32	125.66	202.57	262.48	165.04	98.97
Aug. 2023	152.12	125.63	194.55	259.73	161.43	98.99
Sep. 2023	151.95	125.58	211.58	257.05	161.78	99.01
Oct. 2023	151.81	125.56	214.88	254.43	162.91	99.03
Nov. 2023	151.70	125.52	250.57	251.88	163.66	99.05
Dec. 2023	151.60	125.50	237.98	249.38	160.39	99.07
Jan. 2024	151.52	125.47	226.99	246.95	185.27	99.09
Feb. 2024	151.45	125.46	217.40	244.57	149.04	99.10
Mar. 2024	151.39	125.43	209.01	242.25	132.31	99.12
Apr. 2024	151.34	125.42	201.69	239.99	120.49	99.13
May 2024	151.30	125.40	195.30	237.78	119.17	99.15
Jun. 2024	151.27	125.39	189.72	235.62	121.66	99.16
Jul. 2024	151.24	125.37	184.85	233.51	126.03	99.18
Aug. 2024	151.22	125.36	180.59	231.46	140.37	99.19
Sep. 2024	151.20	125.35	176.87	229.45	143.51	99.20
Oct. 2024	151.18	125.34	173.63	227.50	159.43	99.21
Nov. 2024	151.17	125.33	170.79	225.59	161.71	99.22
Dec. 2024	151.16	125.32	168.31	223.72	191.80	99.23
Jan. 2025	151.15	125.31	166.15	221.90	184.35	99.24
Feb. 2025	151.14	125.31	164.26	220.13	177.90	99.25
Mar. 2025	151.13	125.30	162.62	218.39	172.30	99.26
Apr. 2025	151.13	125.30	161.18	216.70	167.44	99.27
May 2025	151.12	125.29	159.92	215.05	163.22	99.28
Jun. 2025	151.12	125.29	158.82	213.44	159.57	99.29
Jul. 2025	151.12	125.28	157.86	211.87	156.40	99.30
Aug. 2025	151.11	125.28	157.02	210.33	153.65	99.31
Sep. 2025	151.11	125.28	156.29	208.83	151.26	99.31
Oct. 2025	151.11	125.27	155.65	207.37	149.19	99.32
Nov. 2025	151.11	125.27	155.10	205.94	147.40	99.33
Dec. 2025	151.11	125.27	154.61	204.55	145.84	99.33

The chosen candidate will utilize the ARMA model for forecasting. Within this model, the determination of p (order of the autoregressive polynomial) and q (order of the moving average polynomial) is critical. In the context of this particular commodity, it appears that ARMA(1,24) stands out as the most appropriate choice. This decision is based on the consideration that ARMA(1,24) involves the fewest parameters among the candidate models, making it a practical and efficient option for conducting forecasts in this commodity context.

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The data analysis of projected prices for various agricultural products in the Philippines reveals distinct trends. Native garlic and imported garlic, spanning from 2018 to 2022 and forecasted for 2023 to 2025, show no clear upward or downward trajectories, suggesting limited value in their future price forecasts. In contrast, onion creole exhibits a significant and consistent downward trend in retail prices from 2018 to 2022, implying a continued decline in the coming years based on the forecasts for 2023 to 2025. White onion also displays a slight downward trend in prices, indicating a potential decrease in the future. Native onion, however, follows a more intricate pattern with periodic fluctuations, suggesting potential price increases in December for 2023 and 2024 but gradual decreases as the new months begin. Finally, ginger, like garlic, shows no distinct trend from 2018 to 2022 or in its forecasted prices for 2023 to 2025, implying limited predictive value and market impact. These diverse price trends have implications for market dynamics and consumer behaviour in the Philippines.

5. Conclusions and Recommendation

In conclusion, the ARMA Model employed for forecasting Agri-Food Condiments prices yielded reasonably acceptable forecasts. The price trends for Native Garlic, Imported Garlic, and Ginger did not display clear upward or downward trajectories, suggesting that the forecasted prices may have limited value or impact in the upcoming years. Conversely, White Onion and Onion Creole exhibited a declining trend, while Native Onion exhibited a fluctuating pattern of both upward and downward trends. These fluctuations are influenced by various factors, including seasonal production patterns, importation dynamics, economic disruptions resulting from COVID-19, and recent supply and demand issues related to onions in the Philippines.

To enhance the accuracy of Agri-Food Condiments price estimates, it is advisable to undertake further research and explore alternative forecasting models.

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