RESEARCH ARTICLE OPEN ACCESS

Production Patterns of Agricultural Crops in Northern Mindanao: A Time Series Analysis Using ARIMA and GRETL

David Matthew S. Balat [1], Mark Jeryl H. Omandam [2], Ricardo Carlos T. Cañete [3], Dr. Florence Jean B. Talirongan [4], Goldah Grace, Dela Peña-Sultan[5]

--************************----------------------------------

Abstract:

Agriculture is integral to the economic stability and food security of Northern Mindanao, where the region is recognized as a significant producer of an array of crops such as bananas, young coconut, and mango. The present study utilized the ARIMA model in conjunction with Gretl software to project crop yields from 2024 to 2035, drawing on historical data from the Philippine Statistics Authority. The model examined historical trends to anticipate future production, recognizing seasonal patterns and long-term consistency among key crops. The results indicated stable production trajectories for certain crops, such as mango, whereas others displayed moderate variability. These projections offer practical insights for policymakers, farmers, and stakeholders to improve decision-making processes and formulate strategies to alleviate risks linked to yield fluctuations. The recommendations are in the following ways: integrating forecast data into the agricultural planning processes, including additional variables into the subsequent research, and developing data-driven initiatives that increase the farm resilience of the region.

Keywords **— ARIMA model, Gretl software, crop yield forecasting, Northern Mindanao, agricultural production, time series analysis, food security, agricultural resilience.**

--************************----------------------------------

I. INTRODUCTION

Agriculture is crucial to the Philippines' economic growth and food security, and it makes significant contributions to livelihood and regional development [1]. The sector is vital to the economic stability of Northern Mindanao, which is known for its fertile soils, pleasant climate, and diverse agricultural practices. Northern Mindanao, being a producer of young coconut, banana, calamansi, lanzones, mango, papaya, pomelo, rambutan, santol, marang, cassava, and malunggay leaves, makes a substantial contribution to the country's food security and agricultural production. However, the sector is facing a variety of challenges, including climate change, shifting market demand, and the need for environmentally responsible operations. Notably, an estimated 70% of the world's poor live in rural regions and rely mostly on agriculture for a living [2], highlighting the importance of agricultural efficiency both globally and regionally.

Understanding crop production trends can help solve such problems and ensure long-term sustainability in agriculture. As stated in [1], most seasonal trends, farming practices, and market demands can all be broken down to help optimize resource use and gain productivity while still mitigating the risk associated with supply shortages and inefficiency. While general statistical analysis finds value in identifying trends in agriculture, most modern and dynamic features in agricultural data require more developed analytical tools. This study aims to analyze crop production trends in Northern Mindanao, a region known for producing key crops such as young coconut, banana, calamansi, lanzones, mango, papaya, pomelo, rambutan, santol, marang, cassava, and malunggay leaves. Agriculture is crucial to the Philippines' economic stability and food security, so addressing challenges like climate change, shifting market demands, and sustainability is vital. Utilizing Autoregressive Integrated Moving Average (ARIMA) modeling [3], this research examines historical crop production data from 2019 to 2023 to identify seasonal trends, long-term patterns, and potential anomalies. Insights from this study will guide policymakers, farmers, and stakeholders in optimizing resource allocation, improving productivity, and mitigating risks. Ultimately, the findings contribute to fostering sustainable agricultural development and resilience in the region.

II. Theoretical Framework

A. *Review of Related Literature*

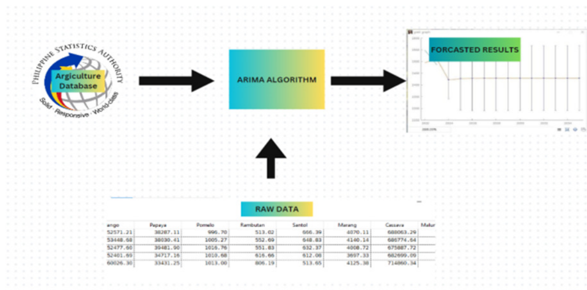
Several research investigations have checked the application of sophisticated statistical methodologies for the analysis and projection of agricultural trends. To illustrate, [3] applied ARIMA modeling to predict banana production in Eastern Visayas, hence showing its adequacy in identifying trends of production patterns and aiding stakeholders in strategic decision-making. In a similar direction, [2] have explored the impact of climate-smart agricultural practices and field schools on the development of farmers' adaptive capacity toward climate change, emphasizing the pressing need for sustainable and resilient agricultural technology in climate-sensitive regions such as Mindanao. Other researchers have highlighted the challenges of the global as well as regional agricultural systems. For example, [1] emphasized the critical need to examine seasonal patterns, market conditions, and agricultural methods to enhance resource distribution and reduce inefficiencies. Furthermore, the World Bank indicated that 70% of the impoverished rural population globally relies on agriculture for sustenance, highlighting the worldwide relevance of agricultural efficiency and sustainability [2].

This research pools into various knowledge streams. Employing ARIMA modeling to forecast the crop production trends of Northern Mindanao from 2019 to 2023 will be very instrumental in adding more information. ARIMA allows for the understanding of the dynamics of past and current productions by making predictions that would thus direct long-term strategic planning. Not only is the seasonality and time dependence of agricultural products like young coconut, banana, calamansi, lanzones, and cassava telling of drivers of yield variability, to say climate change, market demand, or availability of resources, but rather it is essential for targeted designs of interventions on specific regions and addressing productivity, risks, and food security improvements. This study strives to produce a holistic framework for sustainable agricultural development in Northern Mindanao by integrating the findings with the regional agricultural policies and practices, thus underlining the global importance of agricultural efficiency and sustainability.

III. Operational Framework

This study is systematic in crop output observation and prediction for the period of 2019 to 2023 in Northern Mindanao. The database for historical crop yield from crops such as coconut, banana, calamansi, lanzones, mango, papaya, and others was sourced from the Philippine Statistics Authority (PSA). It then pre-processed the data by dealing with missing values as well as outliers in consideration that those could otherwise be a source of inaccuracy. The ARIMA algorithm was used to develop models that enabled the discovery of seasonality fluctuations and persistent crop yield tendencies. This study is based on raw crop yield data to guide the analysis. The predictions created by the ARIMA model prove vital information for aiding decision-making by farmers, policymakers, and other stakeholders. Figure 1 is the framework applied in this research for operations.

Figure 1. Outline design of the Study



IV. Materials and Methods

A. Materials

The statistical information needed for this study was obtained from the Philippine Statistics Authority (PSA) in 2024. The dataset includes historical crop yield statistics for Northern Mindanao from 2019 to 2023, with an emphasis on significant crops such as young coconut, banana, calamansi, lanzones, mango, and papaya. Includes the seasonal and annual yield data, which serve as the foundation for the study. This complete dataset had been processed to remove missing values and abnormalities, ensuring the accuracy of the forecasting process. In addition, contextual data on agricultural practices, market situations, and environmental factors were used to supplement the statistical study [4].

B. Methods

The model used in this study is the ARIMA model, which has been proven to be effective in analyzing and predicting time series data of all types in different domains [5]. It was used to analyze historical agricultural yield statistics and to give forecasts regarding future trends in Northern Mindanao. The evaluation was conducted using Gretl software, which provided a comprehensive and convenient environment for time series modeling. It proved useful in preprocessing data, estimating ARIMA parameters, and generating precise forecast values. Time-series-based forecasting involves a study of the patterns within past data, like seasonal changes and long-term trends, to build up statistical models capable of much approximation in terms of future events. This ensured the accurate estimation of parameters with Gretl's efficient computation, hence ensuring very reliable and easy-to-interpret results.

V. *RESULTS AND DISCUSSION*

Table 1. Raw data of Other Crops: Volume of Production in Northern Mindanao (2019-2023)

Crops	2019	2020	2021	2022	2023
	Annual	Annual	Annual	Annual	Annual
Young Coconut	7,293.40	7,281.81	7,461.51	7,753.70	8,197.50
Banana	1,964,148.18	1,977,157.06	2,016,302.92	2,037,380.83	2,032,525.18
Calamansi	2,349.71	2,371.89	2,471.39	2,548.22	2,485.84
Lanzones	6,510.70	5,144.50	2,913.11	2,045.12	9,008.55
Mango	52,571.21	53,448.68	52,477.60	52,401.69	60,026.30
Papaya	38,287.11	38,030.41	39,481.90	34,717.16	33,431.25
Pomelo	996.70	1,005.27	1,016.76	1,010.68	1,013.00
Rambutan	513.02	552.69	551.83	616.66	806.19
Santol	666.39	648.83	632.37	612.08	513.65
Marang	4,070.11	4,140.14	4,008.72	3,697.33	4,125.38
Cassava	668,063.29	686,774.64	675,887.72	682,699.09	714,860.34
Malunggay Leaves	7,382.83	7,424.83	7,426.47	7,297.38	7,479.00

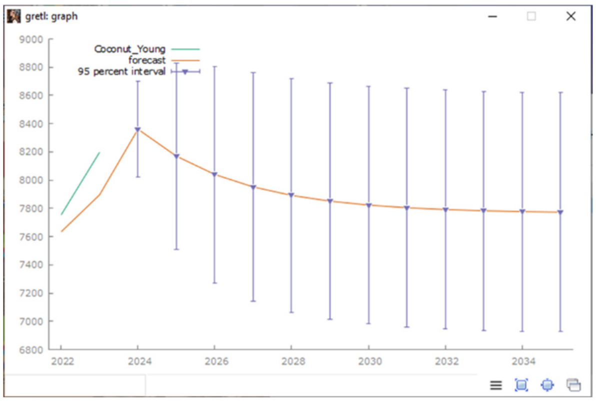


Figure 2. Forecasted Volume of Crop Production - Young Coconut production from (2024-2035)

Figure 2 depicts the ARIMA model's projection with a 95% confidence level for "Banana" from 2024 to 2035. The projection had been close, with numbers trending down over the years until they became stable at 2,002,455.59 in 2035. From there, by moving further into the future, the standard error somewhat increases during the prediction period.

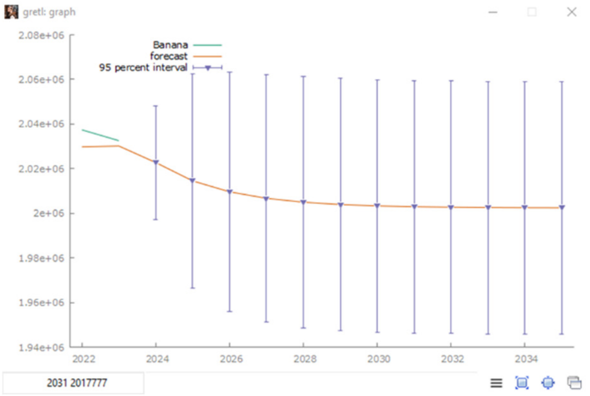


Figure 3. Forecasted Volume of Crop Production - Banana production from (2024-2035)

Figure 3 shows the ARIMA model forecasts and 95% confidence intervals of the variable "Banana" between 2024 and 2035. The estimates were pretty accurate, as values trended in a declining manner over time until 2035 when they stabilized at 2,002,455.59. We see that as we go further into the future, we increase the standard error margin a bit along the horizon of our prediction

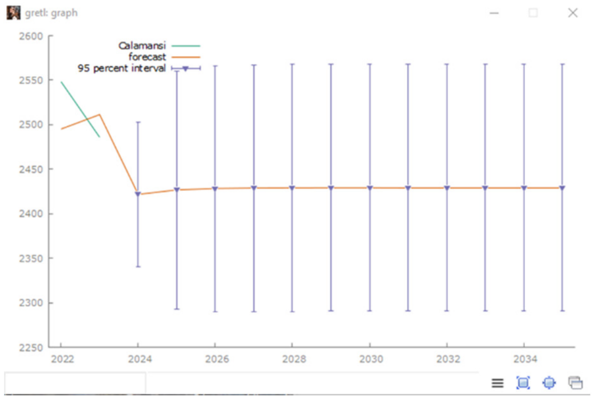


Figure 4. Forecasted Volume of Crop Production - Calamansi production from (2024-2035)

Figure 4 shows a 2a 024-2035 prediction and a 95 % confidence interval for "Calamansi" based on an ARIMA model. It can be observed that over the forecasting horizon, the predictions are very stable, stabilized after some initial fluctuations around 2,429.04 from 2029 to 2035. Standard error grows at first but stabilizes afterward and allows long-term consistent forecasts with minimum uncertainty. Forecast The values for "Calamansi" are stable with minimal uncertainty; hence, a persistent long-term trend exists.

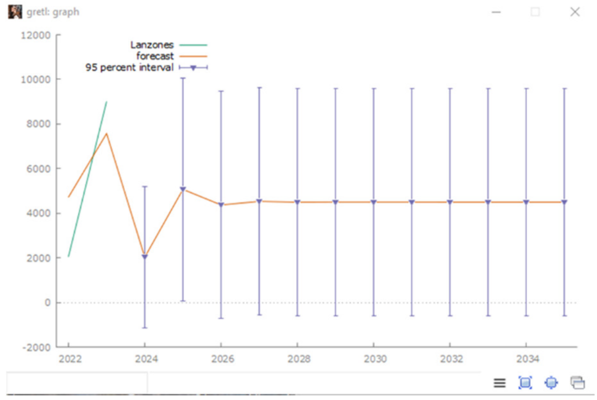


Figure 5. Forecasted Volume of Crop Production - Lanzones production from (2024-2035)

Figure 5 represents the projections with the 95% confidence intervals for the series "Lanzones" from 2024 to 2035, based on an ARIMA. The projection shows volatility in the short run but stabilizes to a point of 4,498.99 starting from 2029. However, the large standard error and widely spreading confidence bands indicate a large amount of uncertainty, especially in the initial years. Although predictions for "Lanzones" have stabilized to about 4,498.99 starting in the year 2029, constant broad confidence intervals point out that great uncertainty exists in these projections. Long-term trends and their accuracy in predicting are, therefore, less dependable

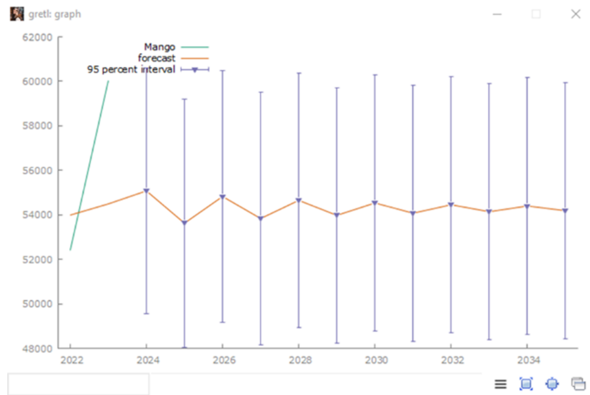


Figure 6. Forecasted Volume of Crop Production - Mango production from (2024-2035)

The graph above, Northern Mindanao's forecasted mango production from 2024 to 2035, depicts generally stable performance during the forecast years. Production is expected to be generally stable at about 54 000 mt/yr with slight fluctuation.

The 95 percent confidence interval has values that range approximately between 48,000 and 60,000 mt for most years, indicating moderate uncertainty. For example, in 2024, output is expected to be 55,074 metric tons, with a margin of error between 49,568 and 60,581 metric tons. The general trend is stable, though the wide confidence intervals are indicative of spiky fluctuations and uncertainty that might have contributed to influencing mango production: climatic variability, market fluctuations, or other farming practices.

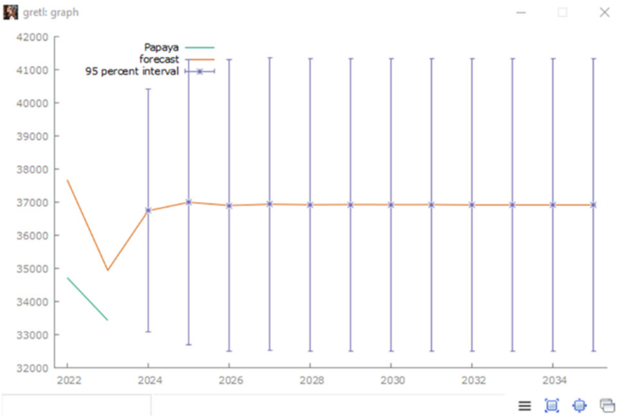


Figure 7. Forecasted Volume of Crop Production - Papaya production from (2024-2035)

Figure 6 shows an annual projection of papaya production for the years 2024 to 2035 based on projection and a 95% confidence interval for each year. For example, in the year 2024, the projection of papaya production is estimated to be 36,742.07, with high confidence being set between 33,074.59 and 40,409.56. That would mean that within this range, 95% sure to be the actual output. The projections between 2025 and 2035 are stable, with an average of 36,926.27, while the respective yearly confidence intervals, although between 32,510.41 and 41,342.88, are still estimated. This means that the optimistic trend expected during the forecast period for papaya production will have a relatively low standard error, which indicates negligible variability in the estimates.

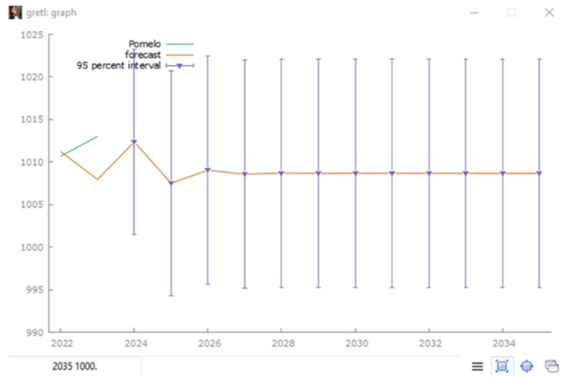


Figure 8. Forecasted Volume of Crop Production – Pomelo production from (2024-2035)

Figure 8 shows the expected pomelo supply from 2024 to 2035, including respective years' 95% confidence intervals. For example, the value that represents a forecast for the year 2024 is s,012.36; this means that the actual production for such a year might fall within the interval of 1,001.47 to 1,023.24. This indicates that the yearly output can remain at a plateau between 2029 and 2035 and be approximately 1,008.67. Minimal deviations are noted as the standard error is very minimal and fluctuates at around 6.845 yearly. The pomelos yield holds steady in the projection period, and the range in the confidence interval is within 95 percent.

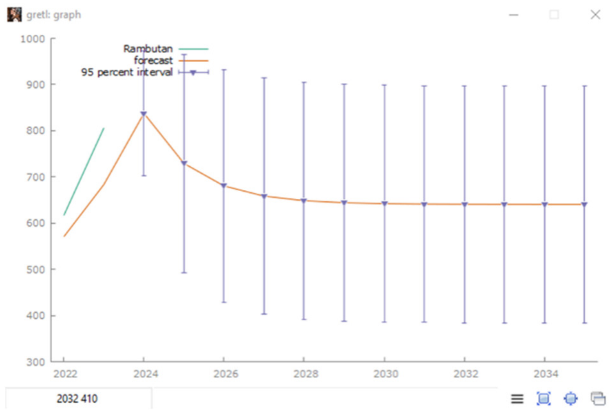


Figure 9. Forecasted Volume of Crop Production - Rambutan production from (2024-2035)

Figure 9 shows annual forecasts of rambutan production from 2024 to 2035, along with the associated 95% confidence intervals. For example, the forecasted output of rambutans for the year 2024 is 837.60; it falls between 703.14 and 972.06, meaning that 95% of the time, a value within that range would be obtained. The projections are modestly downward sloping from 2025 onward, given that the output projections decline progressively from 729.11 in 2025 to 640.42 in 2035. The wide enough confidence intervals for every year ensure some degree of uncertainty, but the upper limits fall between 896.80 and 972.06, whereas the lower bounds often fall between 384.04 and 492.28.

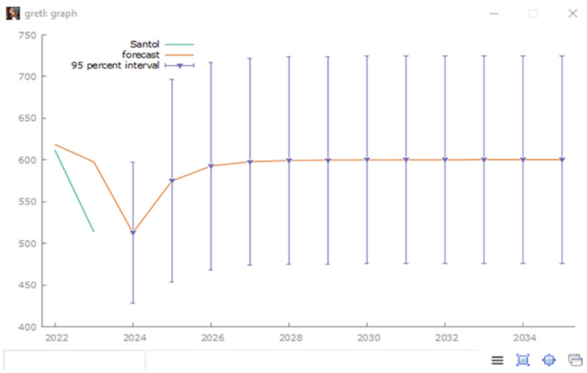


Figure 10. Forecasted Volume of Crop Production - Santol production from (2024-2035)

Figure 10 has the expected Santol productions for the years 2024 to 2035 and 95% confidence for each year. The estimated output for the year 2024 is 512.79, with a 95% confidence interval of 428.15 to 597.42, thus showing that production will most likely be within this given range. In the following years, it is expected to have slight production growth, from 574.75 in 2025 up to 599.95 during 2034 and 2035. That is a relatively strong forecast supported by a narrow uncertainty band: the confidence intervals for every year are very consistent, within the range of 475.52 to 724.37. From 2028, the standard error is expected to remain constant at 63.484, and no deviation is expected in the forecasts for the following years.

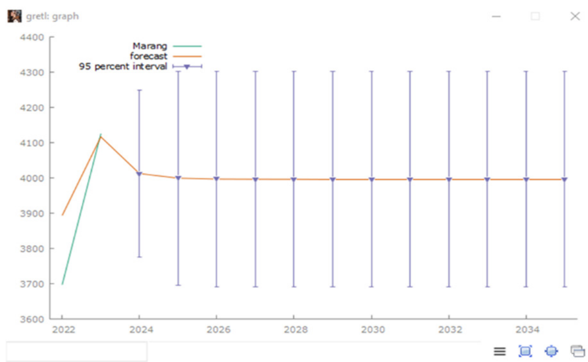


Figure 11. Forecasted Volume of Crop Production - Marang production from (2024-2035)

Figure 11 provides yearly projections of marang output from 2024 to 2035, along with their respective 95% confidence intervals. The actual output falls within the projected production of 4,012.20 for the year 2024, with a 95% CI of 3,776.18 to 4,248.22. Based on consistent projections over time, the production is always seen as projected at 3,996.15 between 2029 and 2035. The predictions seem steady despite the fact that the confidence intervals for each year remain constant at 3,690.67 and 4,301.63.

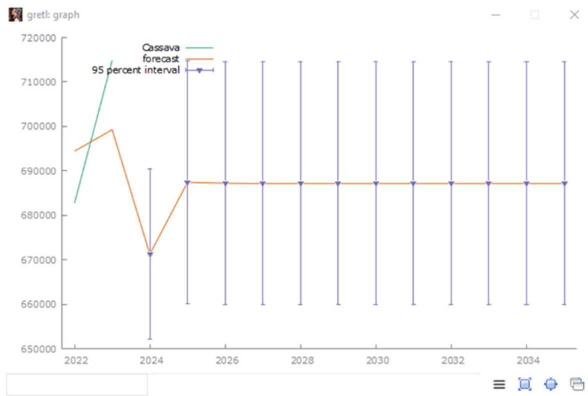


Figure 12. Forecasted Volume of Crop Production - Cassava production from (2024-2035)

Figure 12 represents the 95% confidence intervals obtained from the yearly predictions of the production of cassava from 2024 to 2035. For instance, the estimated output for the year 2024 is around 671,254.28, while its 95% confidence interval ranges between 652,096.54 and 690,412.02, indicating that the actual production falls within that range. The projections in the succeeding years exhibit stability, retaining the same estimate of 687,209.38 starting from 2025 to 2035. In addition, the confidence intervals for the annual level starting from the year 2025 remain stable and range between 659,942.76 and 714,476.00, which implies that the forecasted output levels do not fluctuate much.

Figure 13. Forecasted Volume of Crop Production - Malunggay Leaves production from (2024-2035)

Figure 13 shows the predicted production of malunggay leaves from 2024 to 2035, which is graphed here with a 95% confidence interval. For example, for the year 2024, the predicted output would be 7,355.98, and the 95% confidence intervals are 7,300.69 to 7,411.27-actually the output should be within this range. Almost similarly with variation, as one can see here, projections go on, around 7,394.02 in 2028 to 7,396.32 in 2031. These confidence intervals are also time-invariant and measure up to 7,287.53-7,504.43 since 2028.

VI. CONCLUSIONS

The study efficiently used ARIMA modeling methodologies to anticipate agricultural production patterns in Northern Mindanao, emphasizing significant crops such as coconut, bananas, and mango. The examination concluded that ARIMA effectively recognized past trends and forwarded yields, which provided vital information for planning and decision-making. The production for some crops like mango, calamansi, and malunggay leaves has been stable, while other crops like cassava show a tendency to increase with much better cultivation practices. Banana and rambutan manifest a declining trend, perhaps due to environmental challenges or possible shifts in market demands, and variable crops like lanzones and santol needed adaptation approaches. Thus, this study emphasizes statistical models as significant factors in developing the management of agricultural resources and filling disparities in production. Missing elements include such external factors as climate information and market dynamics whose future areas for improvement make it possible to create more comprehensive forecasting models useful for promoting agricultural sustainability and resilience within the area.

This suggests to policymakers and agricultural planners, including agencies such as the Department of Agriculture (DA) and the Philippine Statistics Authority (PSA), that the predicted data should be used to formulate proactive measures mitigating production variability and ensuring food availability in Northern Mindanao. Initiatives to assist farmers during expected periods with reduced yields should be established to fortify the agricultural economy. Future studies are also recommended to include additional variables, such as climatic conditions and market dynamics, to improve the accuracy and reliability of ARIMA-based forecasts. Further, the exploration of hybrid forecasting models that integrate machine learning techniques with ARIMA can also improve predictability. Further, it is also necessary to have accessible training facilities for farmers and related stakeholders in handling forecast data to improve crop management and planning. A central database of streamlined updates on the region's agricultural production will help improve decision-making and foster a resilient agricultural sector.

REFERENCES

[1] Of Inventory et al. 2021. "Inventory of High Value Crops Using Lidar Data.": 183–87.

[2] Chandra, A., Dargusch, P., McNamara, K. E., Caspe, A. M., & Dalabajan, D. (2017). A study of climate-smart farming practices and climate-resiliency field schools in Mindanao, the Philippines. *World Development*, *98*, 214-230

[3] Bustaliño, B. D., Galos, T. C., & Cajudo, S. G. (2024). Arima Modeling and Forecasting of Banana Production in Eastern Visayas, Philippines: 2010-2022.

[4] Liu, Z., Zhu, Z., Gao, J., & Xu, C. (2021). Forecast methods for time series data: a survey. *Ieee Access*, *9*, 91896-91912.

[5] Mehrmolaei, S., & Keyvanpour, M. R. (2016, April). Time series forecasting using improved ARIMA. In *2016 Artificial Intelligence and Robotics (IRANOPEN)* (pp. 92-97). IEEE.

