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Estimating the Maximum Yield of Rice Produce Using Hybrid ARIMA, Artificial Neural Network and ANFIS

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Rholey R. Picaza[1], OCID No. 0000-0001-6172-5329
Ronald S. Decano[2], ORCID No. 0000-0001-9736-5185

[1]Davao De Oro State College, Purok 10, Poblacion, Compotela, Davao De Oro, Philippines
[2]Davao Del Norte State College, Brgy. New Visayas, Panabo City, Davao del Norte, Philippines
[1,2]University of Mindanao, Davao City, Davao del Sur, Philippines

Abstract

This study predicted maximum rice yield in Davao de Oro using time series models: autoregressive integrated moving average (ARIMA), radial basis function neural network (RBFNN), and adaptive neuro-fuzzy inference system (ANFIS). Quarterly rice production data from 2004 to 2024, sourced from DA-PHILRICE, were analyzed to determine production trends, develop best-fit models, and compare forecast accuracy. RBFNN and ANFIS closely follow the actual test data values, demonstrating their ability to capture fluctuations in rice produce. Based on the result, RBFNN is the most accurate model. These findings suggest a need for the Department of Agriculture to implement strategic interventions, including precision agriculture, enhanced irrigation, distribution of climate-resilient varieties, and farmer training on adaptive techniques and resource efficiency, to mitigate the projected decline of rice yields. Action plan and policies were recommended to improve the rice production with series of activities in the province.

Keywords: rice produce, autoregressive integrated moving average (ARIMA), radial basis function neural network (RBFNN), adaptive neuro-fuzzy inference system (ANFIS), Davao de Oro

INTRODUCTION

As an Asian country, rice is an essential crop for the Philippines, acting as a primary food source for millions and a crucial element of the agricultural economy. Nevertheless, the nation's rice produce encounters major obstacles due to a mix of natural disasters, climate change, and human actions. Climate variability, especially shifts in soil moisture due to the El Niño-Southern Oscillation (ENSO), is responsible for approximately 10% of production irregularities (Stuecker et al., 2018). Fast urban growth has transformed 30-50% of rice fields adjacent to cities into non-agricultural purposes, while insufficient irrigation impacts 30% of rice fields, underlining the necessity for better irrigation access and agricultural inputs, potentially boosting yields to 5.50 metric tons per hectare (Mamiit et al., 2021; Taer, 2024). Moreover, climate change intensifies production issues due to pollution and carbon emissions, as research indicates a strong correlation between carbon emissions and reduced rice yields (Teng et al., 2022).

This study aimed to predict the maximum yield of rice produce in Davao de Oro using time series models. Specifically, this study seeks to to forecast the maximum yield of rice production through ARIMA, RBFNN and ANFIS. It seeks to fill the gap by utilizing time series analysis to predict the highest rice yield in Davao de Oro. By employing sophisticated hybrid models such as ARIMA-RBFNN and ARIMA-ANFIS, the study aims to improve the accuracy of yield predictions, thus assisting policy makers and agricultural stakeholders in tackling the twin challenges of population increase and climate effects on rice production. Global patterns also worsen this situation. Export controls imposed by leading rice-exporting countries frequently affect net importing nations such as the Philippines, resulting in increased local prices and restricted availability (Liu et al., 2022). The need to ensure consistent rice production and distribution in the Philippines is, therefore, a crucial issue for food security and poverty reduction.

The growing population exacerbates this problem by increasing the demand for rice, while urban expansion frequently takes over precious farmland, leading to reduced agricultural land and heightened competition for resources (Ariani & Susilo, 2022). Even with a 12.63% rise in rice production in the Davao Region in 2017 (Philippine Statistics Authority, 2018), this regional growth falls short of bridging the national production deficit, requiring ongoing imports. This reliance presents a threat to food security and highlights the necessity for precise yield predictions to more effectively match production with demand and secure economic stability (Urrutia et al., 2019; Nazir et al., 2021).

Climate change adds more challenges to rice production. Severe weather occurrences like tropical storms, heavy rainfall, and simultaneous drought-flood situations endanger agricultural consistency. Cyclones by themselves have led to significant yield reductions, with as much as 32.9% of impacted regions facing substantial crop damage (Shamsuzzoha et al., 2022). Likewise, intense rainfall may lead to a yield decrease of approximately 8%, affecting nitrogen supply and interfering with pollination (Fu et al., 2023). As these risks escalate, having strong forecasting models is essential for enhancing resilience in rice production systems and maintaining a dependable food supply in the face of environmental difficulties (Cepeda, 2023).

Empirical studies consistently demonstrate that hybrid ARIMA-ANN models outperform individual ARIMA or ANN models, providing more accurate forecasts across various fields. Research in volatile financial markets, where time series data is often non-linear and non-stationary, shows that deep recurrent neural networks (RNNs) integrated with ARIMA enhance predictive accuracy by dynamically adjusting to changes in data trends (Yuan, 2024). Similar results have been found in agricultural applications, where the flexibility of ANNs to interpret complex interdependencies between variables leads to higher forecasting accuracy and better adaptability to changing seasonal patterns, as compared to traditional statistical models (Grebovic et al., 2022).

Temperature, rainfall, and humidity have a notable impact on rice production, while extreme weather can increase risks (Navinkumar et al., 2023). Research has indicated a decline in wet season precipitation in certain areas of Bangladesh, which may affect rainfed rice farming. Rice yields are at risk due to the serious threat posed by rising temperatures, especially those exceeding 36°C (Mainuddin et al., 2022). A worldwide examination shows that there is a general trend of rice production and yield increasing in the main rice-producing nations. Nonetheless, panel regression models indicate that ongoing temperature rises could result in reduced production, with rice production being directly affected by rainfall levels, making it vulnerable to flooding and drought occurrences (Joseph et al., 2023).

Recent research shows the benefits of contemporary agricultural techniques compared to conventional methods in terms of effectiveness and output. Precision farming, which utilizes technologies such as AI and IoT, allows for more precise utilization of inputs, resulting in higher crop yields and profitability (Raj et al., 2021). The use of machinery, such as wearable seed and fertilizer applicators, can greatly enhance input efficiencies and yield stability according to Park et al. (2018). Recent farming techniques have resulted in significant increases in crop yields in different areas and for different types of crops, although there has been an increase in the costs associated with these methods (Abisheva & Mussin, 2023). Nonetheless, combining conventional practices with contemporary strategies presents a hopeful solution for sustainable farming, tackling ecological issues while upholding efficiency (Sekhar et al., 2024).

Forecasts made for maximum yield of rice produce in Davao de Oro. Through this, it can show probable figure/s of what would be the future production of rice in succeeding years. By determining the next production, the Department of Agriculture in Davao de Oro would be able to assess and plan for the next decision of maximum yield of rice produce which implies a more significant opportunity in business.

Globally, it would be beneficial as to the result of this study since to estimate forecast of total crop production in advance is very important for determining the prices, export-import policies and also for making possible for the government to take corrective measures of surplus and scarcity in the crops production.

The hybrid ARIMA-RBFNN model combines the strengths of Autoregressive Integrated Moving Average (ARIMA) models and Artificial Neural Networks (ANN), creating a robust tool for time series forecasting, especially in complex environments. ARIMA is well-suited for capturing linear trends in stationary data but often falls short in modeling non-linear or dynamic relationships (Atesongun & Gulsen, 2024). In contrast, ANNs, particularly the Radial Basis Function Neural Networks (RBFNN) and Time-Series Causal Neural Networks (TS-CausalNN), excel in handling non-linear relationships and adaptively process data, providing flexibility in non-stationary time series without requiring strict assumptions about data distribution (Faruque et al., 2024). By combining these two models, ARIMA-ANN harnesses ARIMA’s strength in linear trend analysis and the ANN’s capacity for managing non-linear residuals, leading to a more accurate predictive model.

The study is an essential investigation to improve rice production. The results of this study and the information it will yield would help the Department of Agriculture in Davao de Oro in decision making and financial planning. The forecast information would also serve as basis in providing the need for adequate rice supply of Davao de Oro's constituents. Lastly, this study can be used for more researches regarding forecasting, planning, management and econometric/time series analysis.

METHODS

Dataset. This study utilized secondary and mainly quantitative data since the data is the quarterly maximum yield of rice produce which is measured on metric tons. Sekaran and Bougie (2016) secondary data sources were derived from the information that is already in existence. The secondary data used in this study was sourced from the Department of Agriculture's Philippine Rice Research Institute (PHILRICE), a reliable authority on rice production in the Philippines. The dataset comprises quarterly metric tons rice production figures for Davao de Oro, spanning from 2003 to 2024. The data used in the study was found on the website of DA-PHILRICE. (https://www.philrice.gov.ph/ricelytics/productions/province/82).

Design and Procedure. This study employed a descriptive -forecasting univariate research design. In this method, historical data of only one variable were collected. Time series research design of longitudinal design was used since this study was establishing a baseline measure, describing changes over time, keeping track of trends, forecasting future short-term trends (Salkind, 2010). A graphical representation of the data was essential to determine the direction and pattern. An observation from the graphical representation was analyzed with a goal of inferring what model would be appropriate to represent the research subject (Horvitz et al., 2013).

Radial basis function (RBF) neural network is a single hidden layer feed forward network with linear output transfer functions and nonlinear transfer functions ϕ (·) on the hidden layer nodes. It is like an MLP except that it uses radial basis functions instead of sigmoid functions. There is only a typically bias neuron on the output neuron.

In an autoregressive integrated moving average (ARIMA) Model, the future value of a variable is assumed to be a linear function of past observations and random errors. The linear model that generates the time series is as follows:

$$\Delta^d Y_t = \delta + \varphi_1 Y_{t-1} + \varphi_2 + Y_{t-2} + \ldots + \varphi_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \ldots - \theta q \varepsilon_{t-q}$$

$\Delta = (1 - B)$, B refers to the backward shift operator for $B(Y_t) = B(Y_{t-1})$, and Y_t and ε are the actual value and random error at time t, respectively; δ are constant, $\varphi_i(i = 1, 2, 3, \ldots, p)$ and $\theta_i(i = 1, 2, 3, \ldots, q)$ are model parameters; p and q are integers, often referred as the autoregressive and moving average orders, respectively.

Both ARIMA and ANN models have achieved successes in their own linear or nonlinear domains, respectively. However, none of them is a universal model than can successfully achieve both domains especially for real-world systems that are often nonlinear. Example for this phenomenon is the underlying process of electricity load data which cannot be easily determined because of the linear and nonlinear patterns. Furthermore, using ARIMA and ANN models to complex nonlinear and linear problems respectively may not be adequate for any type of data. Hence, a hybrid model that has both linear and nonlinear modelling abilities is proposed as an alternative method to capture the different aspects of the underlying patterns (linear and nonlinear) and complex autocorrelation structures in the data can be modeled more accurately.

To evaluate the model performance, two types of standard evaluation statistics were employed in this study. These are Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).

Meanwhile, the root mean squared error (RMSE) is a scale-dependent accuracy measure which is the average distance of the actual value of the observation from its predicted value. It is useful for comparing different model estimated from the same realization. RMSE is sensitive to large errors since the squaring process gives disproportionate weight to very large errors. Two or more models could give essentially the same results in most respects. In comparing RMSE, we prefer the model with lower RMSE is more preferred because it fits the available data more closely. Importantly, the model with lower RMSE tends to have a smaller forecast-error variance. On the other hand, the Mean absolute percentage error (MAPE) is a scale-independent accuracy measure which is the average percentage of the absolute value of the distance from the actual observation to the predicted value. This measure has the disadvantage of being finite or undefined when Yt is 0 and extreme values when Yt is close to 0. In comparing several forecasting methods, RMSE and MAPE give different results as to which forecasting method is the best. RMSEs are first compared and if the values are close, the MAPE are compared. In comparing which MAPE is the least, it should also have the least RMSE.

The following steps were undertaken to achieve the objectives of the present study. First, permission to conduct the study was asked from the Ethics Review Committee. When it was granted, the author started gathering publicly available data related to rice production in Davao De Oro in online sources. Second, the author developed his model for forecasting from the three (3) models. These models were candidate models for fitting the observed dataset. Third, the data were encoded in the Microsoft Excel spreadsheet. The models were run by r studio. Fourth is the graphical analysis and interpretation of numerical data. Fifth, it was necessary to validate the model's generalizability; thus, data splitting was undertaken. The models were tested on two sub-samples, and metric measures were compared. The first half served as a training set, while the second half served as a testing set. Lastly, the model with better forecasting ability predicted the rice production in the Davao De Oro, Philippines.

Ethical Considerations. By following the protocol assessments and standardized criteria, the researchers adhered to all ethical norms in conducting of the study.

RESULTS AND DISCUSSION

The test data, comprising 20 percent of the total dataset, was used to evaluate the performance of different forecasting models, including

ARIMA (3,1,1), Radial Basis Function Neural Network (RBFNN), Hybrid ARIMA-RBFNN, and Adaptive Neuro-Fuzzy Inference System (ANFIS). The actual rice production values for each quarter were compared with the predicted values from each model. Among the models, ARIMA (3,1,1) consistently produced lower estimates, with minimal variation in its predictions across different quarters. In contrast, RBFNN and ANFIS showed greater variability, often capturing fluctuations more effectively but sometimes deviating significantly from actual values.

The hybrid ARIMA-RBFNN model generally produced lower predictions compared to RBFNN and ANFIS, indicating that the combination of statistical and neural network approaches did not always enhance predictive accuracy. ANFIS, on the other hand, tended to overestimate rice production, particularly in later years. For instance, in 2022 Q2, ANFIS predicted 37,141.67 metric tons, whereas the actual value was only 23,984 metric tons. Despite these discrepancies, RBFNN and ANFIS were more responsive to fluctuations in production trends.

Table 1
Predicting test data to evaluate model performance.

Date	ARIMA (3,1,1)	RBFNN	Hybrid ARIMA-RBFNN	ANFIS
2020 Q4	30,917.78	30,006.89	29,681.33	30,094.36
2021 Q1	29,793.41	32,331.28	29,099.62	31,176.68
2021 Q2	30,042.50	28,243.73	25,146.26	33,276.40
2021 Q3	30,328.71	32,070.30	29,146.04	33,480.95
2021 Q4	30,309.39	33,600.28	28,062.35	35,447.21
2022 Q1	30,242.23	32,633.25	27,991.29	36,392.95
2022 Q2	30,237.92	31,896.01	26,079.94	37,141.67
2022 Q3	30,252.54	38,904.41	27,579.00	38,340.73
2022 Q4	30,255.40	40,962.09	26,844.89	37,144.80
2023 Q1	30,252.47	34,526.53	27,245.26	35,574.37
2023 Q2	30,251.44	30,602.76	25,886.45	35,992.11
2023 Q3	30,251.97	38,582.95	26,821.38	38,813.00
2023 Q4	30,252.28	39,520.62	26,901.18	37,896.37
2024 Q1	30,252.19	35,912.42	26,884.57	37,094.39
2024 Q2	30,252.12	32,758.83	26,437.80	35,867.42
2024 Q3	30,252.12	40,789.56	26,889.82	37,435.80
2024 Q4	30,252.14	41,255.17	30,580.78	36,262.92

Figure 1 presents the graphical comparison of the model's performance in predicting the test set, with different colors representing each forecasting approach: green for RBFNN, red for ARIMA (3,1,1), violet for Hybrid ARIMA-RBFNN, and yellow for ANFIS. The visual representation aligns with the findings in Table 1, showing that RBFNN and ANFIS closely follow the actual test data values, demonstrating their ability to capture fluctuations in rice production. In contrast, ARIMA (3,1,1) maintains a more stable prediction trend, often underestimating the actual values, while the hybrid model shows a more conservative approach in its forecasts. To determine the most accurate model, these results will be further validated using specific accuracy measures.

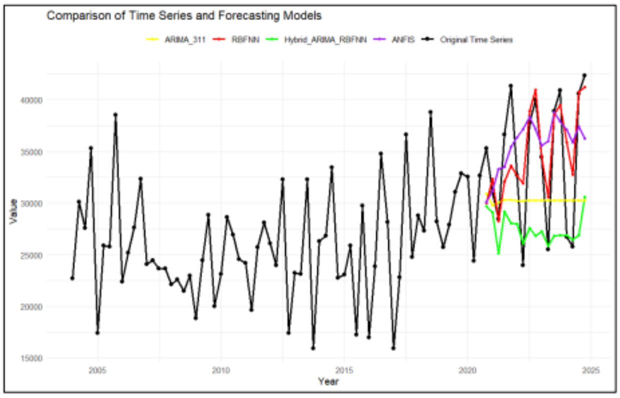

Figure 1
Graphical presentation of model's performance in predicting test set. Green (Hybrid), Red (RBFNN), Violet (ANFIS), Yellow (ARIMA)

The test data, comprising 20 percent of the total dataset, was used to evaluate the performance of different forecasting models, including ARIMA (3,1,1), Radial Basis Function Neural Network (RBFNN), Hybrid ARIMA-RBFNN, and Adaptive Neuro-Fuzzy Inference System (ANFIS). The actual rice production values for each quarter were compared with the predicted values from each model. Among the models, ARIMA (3,1,1) consistently produced lower estimates, with minimal variation in its predictions across different quarters. In contrast, RBFNN and ANFIS showed greater variability, often capturing fluctuations more effectively but sometimes deviating significantly from actual values. the RBFNN model outperformed the other models, achieving the smallest accuracy measures across all metrics. With the lowest MAE (3021.6), MAPE (10.25%), MASE (0.7604), and RMSE (4402.6), RBFNN demonstrated superior predictive accuracy in forecasting rice production in Davao de Oro. Compared to ARIMA, Hybrid ARIMA-RBFNN, and ANFIS, which showed higher error values, RBFNN's performance highlights its effectiveness to predict future quarterly rice produce of Davao de Oro.

Table 2
Predicting test data to evaluate model performance

Date	ARIMA (3,1,1)	RBFNN	Hybrid ARIMA-RBFNN	ANFIS
2020 Q4	30,917.78	30,006.89	29,681.33	30,094.36
2021 Q1	29,793.41	32,331.28	29,099.62	31,176.68
2021 Q2	30,042.50	28,243.73	25,146.26	33,276.40
2021 Q3	30,328.71	32,070.30	29,146.04	33,480.95
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2023 Q4	30,252.28	39,520.62	26,901.18	37,896.37
2024 Q1	30,252.19	35,912.42	26,884.57	37,094.39
2024 Q2	30,252.12	32,758.83	26,437.80	35,867.42
2024 Q3	30,252.12	40,789.56	26,889.82	37,435.80
2024 Q4	30,252.14	41,255.17	30,580.78	36,262.92

The Provincial Government of Davao de Oro will implement the SAGANA Program ("Suporta at Ayuda para sa Ganap na Ani"). This program provides cash assistance and certified high-yield rice seeds to rice farmers across the province. To join, farmers must register with the Provincial Department of Agriculture (PDA) and submit key documents such as land title, valid government ID, and a barangay certification proving active rice cultivation. This ensures that only legitimate farmers are included in the program.

Recommendation. Based on the results, it is recommended that the Department of Agriculture (DA-PHILRICE) must enhance their research on high-yield hybrid rice varieties, adopt precision farming technologies, and strengthen support programs for farmers, focusing on soil management, efficient irrigation, and climate adaptation strategies. Secondly, the Davao de Oro Provincial Government should collaborate closely with agricultural agencies to increase funding for modern farming techniques, promote sustainable land use policies, and provide subsidies for advanced agricultural inputs. Lastly, future researchers should also consider including additional variables such as climate data, pest outbreaks, and economic factors in forecasting models to improve accuracy and identify the main drivers behind the decline in rice production using multivariate time series model.

Plagiarism. This research did not directly copy nor mimic, in any manner, texts and other literatures that could lead to plagiarism. Proper in-text citation and referencing were done to ensure acknowledgement of literary authors. The researchers ensured the use of their own words allowing them to communicate their ideas as anchored from the authors of various studies reflected in the study.

Fabrication. This research was anchored from several high-quality and well-researched studies. It ensured that the researchers did not create personal stories out of their readings and, as a result, asserted the writer's arguments based on their thoughts and understandings. There were no fabrications of data or results, nor is there any deliberate presentation of conclusions. The authors had grounded their work with precision.

Falsification. The author develops and maintains guidelines and high standards for accuracy in the facts reported.

Conflict of Interest. The author declares no conflict of interest.

Technology Issues. The study uses secondary data, which are publicly available online. Ilt does not gather information through online access panels. It does not view any information being transmitted in a digital environment.

Authorship. The researchers recognize the valuable contribution of their adviser, who painstakingly and scholarly critiqued their paper leading to several improvements. They also prepared the research article, critically edited it for a significant intellectual substance, and gave final approval for the published version.

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