Regional Crop Yield Prediction Using Feedforward Neural Networks

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***Abstract*— Crop Yield Prediction or CYP is a crucial aspect of food security. Being able to forecast shortages and excess in crop production can aid consumers in supply management as well as help the government in creating agricultural policies and implementing economic decisions that can help balance the supply chain. This study aims to build a crop yield prediction model using Neural Networks that is capable of handling high-dimensional datasets with complex patterns. The model was trained using crop yield data from the province of Quezon for years 1987-2015, as well as the climatological data observed in the same province for the same period. The model was tested using the same data features that were observed for the years 2016-2022. The forecast performance of the resulting model was benchmarked against two statistical forecasting techniques, namely the univariate Seasonal Autoregressive Integrated Moving Average and the multivariate Autoregressive Distributed Lag using the performance metrics Mean Absolute Error, Root Mean Squared Error, and Mean Absolute Percentage Error. The research findings indicate that the Neural Network-based CYP model performed best for both rice and corn yield forecasting with a MAPE of 3.84% and 4.46%, respectively.**

Keywords—neural networks, time series forecasting, autoregressive, crop yield prediction

I. INTRODUCTION

Time series forecasting has many applications across different industries. From predicting business sales, anticipating the spread of an epidemic, and conducting macroeconomy analytics, classical time series forecasting models such as Autoregressive Integrated Moving Average (ARIMA), Autoregressive Distributed Lag (ARDL), and Exponential Smoothing (ES) have been used extensively in the past decades. Not only are these models (ARIMA, ARDL, and ES) and their variants easy to interpret but they also perform well in applications where datasets have countable and few predictive variables. In fact, institutions commonly employ classical forecasting techniques to predict crop production volumes for rice and corn. These techniques are usually based on an autoregressive approach, which are generally good at handling low-dimensional time series data but tend to decline in performance when applied to extremely complex and nonstationary datasets. Thus, this study explores the use of Neural Networks to create a forecasting model that is theoretically more accurate compared to classical forecasting models. The researcher designed and implemented a Feedforward Neural Network (FNN) forecasting model that can outperform autoregressive models in terms of robustness and adaptability to growing complexities introduced by intricate meteorological conditions. Although this study focuses on the handling of meteorological variables, it can be noted that many physical phenomena like light, sound, and pressure do not always exhibit a simple linear relationship with their measured signal. This extends the applicability of Neural Networks and other machine learning techniques to fields like sensor networks and communication systems, where processing complex and nonlinear sensor or transceiver data is essential.

II. REVIEW OF RELATED LITERATURE

A. Sesonal AutoRegressive Integrated Moving Average (SARIMA)

Autoregressive integrated moving average or ARIMA, is a statistical analysis approach that uses univariate data to better understand a time series and to predict future trends. A statistical model is autoregressive if up to a certain degree, it predicts future values based on past values or if there are temporal dependencies in the time series data. From predicting a stock's future price based on its past prices to trying to forecast a company's future earnings based on its earnings in the past periods, ARIMA has a wide range of applications [1]. SARIMA, a variant of ARIMA which was used in this study, introduces the seasonal component in the model hence the addition of another variable "S" in its name. The researcher opted to use SARIMA because of the observed and tested seasonality in the quarterly crop yield data after performing Kruskall-Wallis test. Shown below in Equation (1) is the general form of a SARIMA equation, where ϕ_p is the non-seasonal autoregressive component, θ_q is the non-seasonal moving average component, Φ_P is the seasonal autoregressive component, Θ_Q is the seasonal moving average component, ε_t is the offset at time t, and B is the backshift operator that produces the past timestep of the AR and MA polynomials.

$$\Phi_P(B^s)\phi_p(B)(1-B)^d(1-B^s)^D Y_t = \Theta_Q(B^s)\theta_q(B)\varepsilon_t \quad (1)$$

B. AutoRegressive Distributed Lag (ARDL)

AutoRegressive Distributed Lag is another classical forecasting technique that is mainly used for analyzing long and short-term relationships between different time series variables. The AR component of the model captures pattern and temporal dependencies in the time series data while the DL component captures the relationship between independent variables X_t and the dependent variable Y while also considering the causality of the lag values of X_t to the present values of variable Y. Note that in the context of this study, the dependent variable Y is the forecasted crop yield while the independent variables X_t are the average rainfall, average

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temperature, humidity, and cloud cover. The general goal of ARDL is to capture the lagged effects of the independent variables X_t to the dependent variable Y [2]. Shown below in Equation (2) is the general form of an ARDL equation. Y_t denotes the dependent variable at time t, X_t denotes the independent variables at time t, αi are the coefficients of Y, βj are the coefficients of the current and lagged X_t, p is the number of lags for Y, and q is the number of lags for X_t.

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{j=0}^{q} \gamma_j X_{t-j} + \epsilon_t \qquad (2)$$

C. Artificial Neural Networks (ANN)

Artificial neural network (ANN) is a machine learning subset that is modeled after the connectivity and functionality of the neurons in the human brain. ANNs are typically comprised of a series of node layers namely the input layer, one or more hidden layers, and the output layer. Each node or neuron can be visualized as its own regression model composed of input data, weights, a bias (or threshold), and an output. These individual nodes connect to all the nodes in the adjacent layers. If the output of any individual node is above the specified threshold value, that node is activated, sending data to the next layer of the network, effectively simulating the flow of brain signals in the neurons of the human brain.

Arguably the simplest type of Artificial Neural Networks, a Feedforward Neural Network (FNN) or Multilayer Perceptron (MLP) allows the flow of information in the node layers in only one direction—forward. The input data gets accepted in the input layer and then the input layer passes it to the hidden layer/s using an activation function. Then, the last hidden layer passes the data to the output layer also through an activation function. These activation functions decide on the neurons that will be used in the flow of information in the network. The input layer has several input nodes that will be configured during the definition of the model. In crop yield prediction applications, these input nodes can correspond to the contributing factors to crop production e.g. meteorological data.

D. Weather and Climate Effects on Crop Production

From the period of land cultivation up until harvesting season, the production of agricultural crops is affected by biotic and abiotic factors. While biotic factors refer to crop diseases and pests, abiotic factors can further be classified into two categories: soil variables and meteorological variables. Soil variables consist of soil fertility, irrigation, ph level, and other less dominant factors. On the other hand, meteorological variables describe the amount of precipitation, amount of sunlight, temperature, and relative humidity that the crops experience and/or receive among others [2]. Like most agricultural crops, rice production is highly dependent on favorable climate. Extreme heat waves during El Niño season cause temperatures to go above 40 °C in Southeast Asian Countries. In such cases, farmers choose to delay the rice planting season to avoid losses as the heat stress caused by such temperature levels is generally too much for plants to handle. Heat stress causes water loss, delayed growth, and seedling death in plants—causing an overall reduction in crop yield [3]. Likewise, excessive rainfall and flooding can also reduce crop production in many ways. Plants that are submerged in water for too long will face extreme levels of imbalance in the exchange of atmospheric gasses that they need to survive. Furthermore, too much rainfall can cause saturation to the soil that, in effect, decreases the roots' ability to absorb nutrients. In both cases, the survival rate of plants and hence total yield is reduced [4]. These cases of extreme changes in meteorological variables become harder to capture when creating a statistical forecasting model as residuals in the time series data gets more sophisticated and as the stationarity of the data gets affected by the changing seasons.

III. Methodology

The implementation of the project was divided into three phases: Data Preparation, Model Building, and Model Evaluation. The Data Preparation phase is comprised of steps that involved raw data gathering, data visualization and preprocessing, and dataset formatting and preparation. Secondly, the Model Building phase is where the FNN, ARIMA/SARIMA, and ARDL forecasting models were built, trained, and tested. Lastly, in the Model Evaluation phase, a comparative analysis of the derived models was done. The forecasting results of all three models were interpreted and assessed using the declared performance metrics to capture the optimal hyperparameter tuning for all the models. For both SARIMA and ARDL, the Akaike Information Criterion (AIC) of both models were also used as basis for determining the best model that was used for benchmarking.

A. Data Preparation

1) Data Gathering: Quarterly rice paddy and corn yield data from the province of Quezon for years 1987-2022 were obtained from the PSA openstat database. Quarterly meteorological data recorded in three PAG-ASA weather stations from the province of Quezon were obtained from DOST PAG-ASA CAD. The climatological observations that were used as meteorological data features for both the ARDL and FNN models are the quarterly average rainfall, temperature, relative humidity, and cloud cover for amount of sunlight.

2) Dataset Formatting: After cleaning the raw data, datasets for respective models were prepared. For SARIMA forecasting model, the dataset used was a .csv file with 3 columns and 145 rows. The first column holds the year label and the second column holds the quarter label. The third column holds the historical crop yield data. Tests for normality, seasonality, and presence of trend were done on the crop yield data, as well as time series transformation to allow for better data visualization.

For the ARDL model, meteorological data were consolidated with the historical crop yield data into a single dataset. This resulted in a final dataset with 7 columns and 145 rows. Time series transformation and test for stationarity were performed for all the data features used. All these transformations and tests for both SARIMA and ARDL were done using R software.

Similarly, the FNN dataset used the same format as the ARDL dataset but with additional columns. These additional columns are the previous quarter yield, previous two quarters yield, previous three quarters yield, and previous year yield. This is to maximize the ability of the neural network to detect temporal patterns and short-term to long-term dependencies in the dataset [5]. With said additional variables present in the FNN input layer, the researcher introduced a memory feature to the model that resulted in improvement in prediction accuracy.

B. Model Building

The researchers used various R packages and Python's StatsModels library to visualize and better understand the dataset and identify stationarity, trends, short-term fluctuations, and seasonality in the time series crop yield data. Shown in Figure 1 is the time series decomposition of the historical rice yield. The observed plot depicts the actual observed historical yield while the plots for trend, seasonal, and random depict the actual trend, observed seasonality or cyclical behavior, and the significant fluctuations in the time series data.

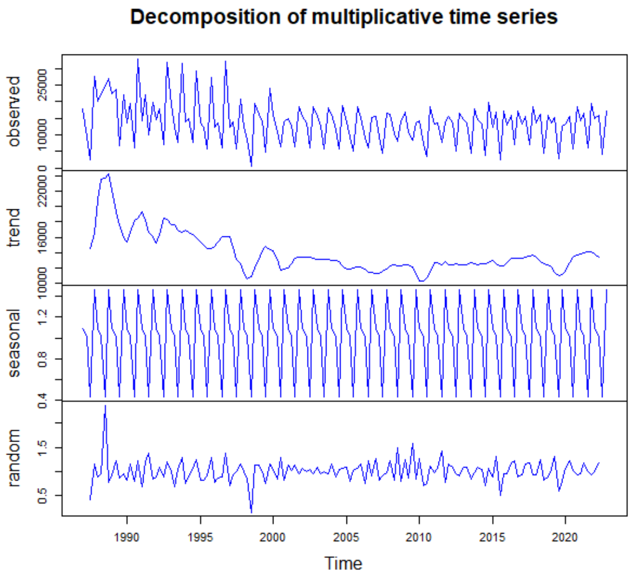

Figure 2: Rice Yield Time Series Decomposition

Since seasonality is present in the crop yield data, a SARIMA time series forecasting model was implemented instead of ARIMA. After performing the Wilk-Shapiro test and Augmented Dickey-Fuller test for stationarity, the PACF and ACF plots of the time series crop yield were inspected by the researcher to determine the AR and MA terms of the model, respectively. The resulting hyperparameter setting for the model is (0,0,0)(2,1,0)[4]. This setting was selected and implemented in the final SARIMA model because it gives the lowest AIC score, and it results in the best forecast performance in terms of the declared metrics. This optimal hyperparameter tuning was verified by using the auto.arima function under the forecast package in R. This will be further discussed in the Results and Discussion section.

For the ARDL model, the time series crop yield was set as the explained variable Y and meteorological variables namely the average rainfall, average temperature, relative humidity, and cloud cover were set as the explanatory variables X_1, X_2, X_3, X_4. Augmented Dickey-Fuller test was conducted for all the mentioned data features to ensure that all variables are stationary. Since all variables were tested to be stationary, there is no need to perform a cointegration test as it is only necessary when there are nonstationary variables. Different lag orders were investigated starting from lag order 1 up to lag order 10, and the lag order that was used in the final model was 9 for both the explained variable Y and all the explanatory variables Xt. This is because lag order 9 gives the best AIC score, as well as it results to the best forecast performance in terms of the declared performance metrics. This optimal lag order was verified by using the lag order selection function VARselect for both the explained variable Y and explanatory variables Xt. The VARselect function under the vars library in R automatically determines the optimal lag length for time series data using the Akaike Information Criterion (AIC), Hannan-Quinn Information Criterion (HQ), Bayesian Information Criterion (BIC), and Final Prediction Error (FPE). This will be further discussed in the Results and Discussion section.

The resulting equation for the ARDL model that was used in the study is shown below in Equation (3), where both the explanatory and explained variables Y and X_t are being lagged up to the order of 9.

$$Y_t = \alpha_0 + \sum_{i=1}^{9} \beta_i Y_{t-i} + \sum_{j=1}^{9} \gamma_j X_{t-j} + \varepsilon_t \qquad (3)$$

Using Python's TensorFlow Keras environment, the researcher defined a sequential Neural Network with densely connected layers. The input layer was designed to have 12 input nodes for crop yield, year, month, quarter, average rainfall, average temperature, relative humidity, cloud cover, same year last quarter yield, same year last two quarters yield, same year last three quarters yield, and same quarter previous year yield.

These input features were transformed using the MinMaxScaler function from the numpy library in order to normalize their values between 0 to 1. The number of hidden layers used was 3, with the rectified linear unit (relU) as its activation function and Adam as its optimizer. As for the output layer, a single output node was used to return yield predictions from the model. The hyperparameters of the final FNN model are described below:

- Epochs: 1000
- Batch size: 32
- Learning rate α: adaptive
- Hidden Layer Activation Function: relU
- Output Layer Activation Function: linear
- Optimizer: Adam
- Loss Function: Mean Squared Error

The final Feedforward Neural Network architecture that was implemented is shown below in Figure 2.

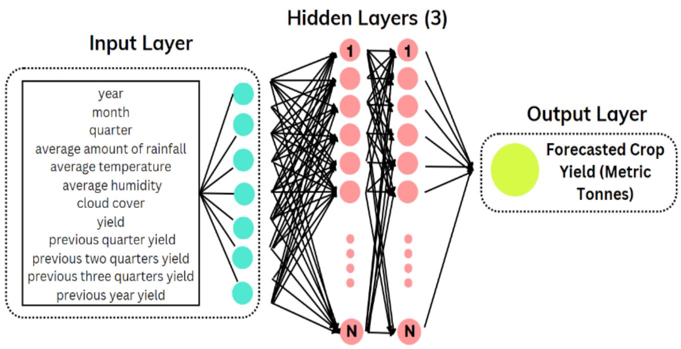

Figure 1: FNN Final Architecture

C. Model Evaluation

For all three models, a rounded-off data split of 81-19 for training and testing was implemented. 80.56% of total data corresponds to 28 years of training set while 19.44% of total data corresponds to 7 years of test set. The test set was used to evaluate the performance of all models using the performance metrics Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE).

For SARIMA, model diagnostics such as the mean zero t-test, ArchTest for variance constant, Jarque-Bera test for normality of errors, and ACF-PACF inspection on model residuals were done to ensure model adequacy and to validate initial assumptions about trend, seasonality, and stationarity. For ARDL, an added Breusch-Godfrey serial correlation LM test was done to ensure adequacy of the ARDL model. The Akaike Information Criterion (AIC) was used in model selection for both SARIMA and ARDL as it is a good measure of how well models fit the training data with the fewest possible parameter adjustments. The SARIMA and ARDL models with the best AIC-forecast error balance were chosen as the final models.

All three models were trained and tested using the rice yield data that was obtained from PSA. Then, all models were re-trained and re-tested using the corn yield data to compare forecast accuracy and to extend the scope of the study to corn yield forecasting. Additionally, the models were tested using varying test set sizes to capture changes in forecast accuracy with varying forecast horizon lengths.

IV. RESULTS AND DISCUSSION

A. SARIMA

The resulting best model for SARIMA in terms of forecast error with MAE 2061.16 metric tons, MAPE 21.69%, and RMSE 2422.01 metric tons was achieved by the hyperparameter setting (p,d,q)(P,D,Q)[m] = (0,0,0)(2,1,0)[4]. With a forecast horizon of 7 years or 28 quarters (2016-2022), the superimposed plot of this forecast is shown below in Figure 3.

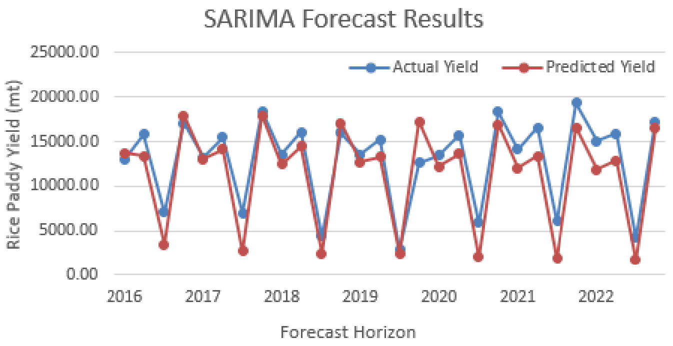

Figure 3: SARIMA Forecast Results

After conducting model diagnostics, it has been shown that with α = 5%, the model failed to reject the Ho that the mean of the model residuals is zero. With Chi-squared value of 31.163 and α = 5%, the model is shown to have rejected the Ho that the variance of the residuals is constant. Furthermore, the Jarque-Bera test that was conducted shows normality of errors while the Ljung-Box test failed to reject the Ho that there is independence of errors in the model residuals. With all the diagnostics conducted showing model adequacy and low enough AIC score of 2158.725, the hyperparameter setting (0,0,0)(2,1,0)[4] was chosen as the final tuning for the SARIMA model.

B. ARDL

The resulting best model for ARDL in terms of forecast error with MAE 1762.37 metric tons, MAPE 14.56%, and RMSE 2309.85 metric tons was achieved by the hyperparameter setting (p,q) = (9,9). This corresponds to lag order = 9 for both the explained variable Y (crop yield) and the explanatory variables X_1, X_2, X_3, and X_4 (average rainfall, average temperature, relative humidity, and cloud cover). With the same forecast horizon as the SARIMA model, the superimposed plot of this forecast is shown below in Figure 4.

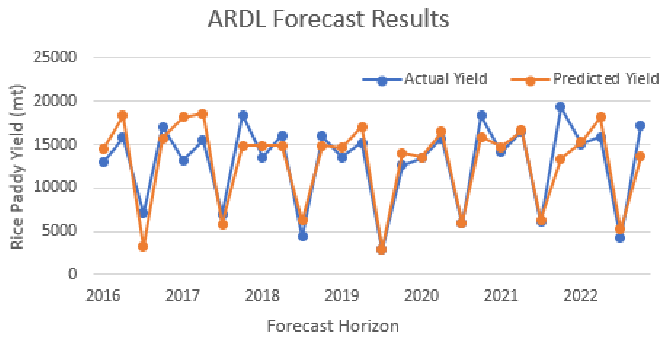

Figure 4: ARDL Forecast Results

Since the explanatory variables *Xt* are technically being regressed to the explained variable *Y* in ARDL forecasting, the Breusch-Godfrey serial correlation LM test was conducted together with the PACF inspection as part of the model diagnostics. The BG test showed an LM test statistic of 0.16375 and a p-value of 0.85928, thus failing to reject the Ho that there is no serial correlation of up to lag 1 in the residuals of the ARDL model. This, coupled with the fact that there are no significant errors in the model residuals in its PACF plot and an AIC score of 2548.47, indicates that the assumptions about the data features are correct. This includes the assumption about stationarity of the explained variable *Y* and all the explanatory variables *Xt*, as well as the optimal lag order that was used in building the model. Moreover, model diagnostics p-value inspection shows that at α = 0.05, the only statistically significant variables in the chosen model are the crop yield lags 1, 4, 7, 8, 9; rainfall lags 1 and 8; temperature lag 1; relative humidity lag 7; and cloud cover lag 7. Because of this, reruns on the model at different lag orders with varying input features were done.

C. Feedforward Neural Network (FNN)

For FNN, the resulting best model in terms of forecast error with MAE 355.84 metric tons, MAPE 3.81%, and RMSE 605.49 metric tons was achieved at neural network setting of epoch = 1000, batch size = 32, and adaptive learning rate α. By adjusting said hyperparameters and making them higher, the risk of overfitting the model also increases. This is the reason why the researcher opted to use the Neural Network setting described in the Methodology section as the final architecture for the FNN model. With the same forecast setting as the other two statistical models, shown below in Figure 5 is the plot of this FNN forecast superimposed with the test set.

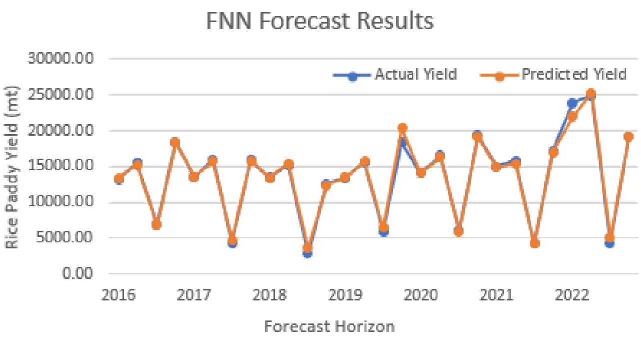

Figure 5: FNN Forecast Results

D. *Comparing the Forecast Results*

To benchmark the FNN model performance against the other two models, Table 1 below presents the rice paddy yield forecast accuracy of all three models in terms of MAE, MAPE, and RMSE.

Table 1: Rice Paddy Yield Forecast Results

Model	Performance Metrics		
	MAE (mt)	MAPE (%)	RMSE (mt)
SARIMA	2061.16	21.69	2422.01
ARDL	1762.37	14.56	2309.84665
FNN	355.84	3.81	605.49

Now that testing and training were done for all models, results show that the FNN model is the most accurate in terms of forecast error. Careful inspection of the forecast plots for both the SARIMA and ARDL models reveals that forecast errors of both models often peak at quarters when crop yield is at either the annual minimum or maximum. This hints weakness in the models' ability to capture extreme observations in the dataset. Meanwhile, the plot of the FNN model shows that forecast errors at quarters when the crop yield is at the minimum or maximum are significantly less, resulting in an overall better forecast accuracy. This aligns with the researcher's hypothesis that machine learning models particularly Neural Network-based ones, are better at capturing abrupt and extreme changes in the time series data.

Another important aspect that was investigated by the researcher is the performance of all the models when forecasting with different test set sizes or essentially varying forecast horizon lengths. Shown below in Table 2 are the MAE and MAPE of the models with forecasting horizon lengths of 1 year up to the original test set size of 7 years.

Table 2: Forecast Results for Varying Forecast Horizon

Forecast Horizon (years)	MAE (mt) and MAPE (%)					
	SARIMA		ARDL		FNN	
1	625	5.5	2419	26.6	9011	84.2
2	1962	16.1	2594	24.2	6504	75.8
3	1921	16.3	2497	23.3	784	6.9
4	1158.	14.7	2171	21.7	4958	38.4
5	1134	15.9	2165	19.8	273	2.1
6	1054	13.0	1961	17.2	591	4.9
7	2061	21.7	1762	15.1	355	3.8

The SARIMA model performed best when the forecast horizon length was set to 1 year. Meanwhile, the ARDL model performed second best in the same forecast horizon length and the FNN model performed worst. This result regarding the forecast accuracy of the SARIMA and FNN models contrasts with the result when the forecast horizon length was set to the original test set size of 7 years, as shown in Table 1. An insight that can be drawn from this is that univariate time series forecasting methods such as SARIMA may tend to perform better at short-term forecasting applications compared to multivariate forecasting techniques and neural network-based models. Also, an interesting observation that was made by the researcher is that there was a slight trend of improvement on the forecast accuracy of the ARDL model while there was a significant improvement on the forecast accuracy of the FNN model with increasing forecast horizons. This hints strength and superior robustness of both models when used in long-term forecasting applications. Refer to Figure 6 for a better illustration of this relationship.

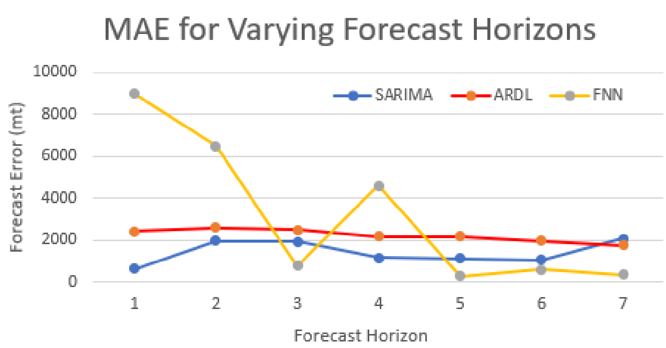

Figure 6: Comparison at Varying Forecast Horizons

E. *Extending the Models to Corn Yield Forecasting*

The final SARIMA, ARDL, and FNN models were used to forecast corn yield using the quarterly corn yield data that was obtained from the PSA *Openstat* database. Using the same train-test data split, the SARIMA model was trained with the time series corn yield data from the province of Quezon that spans from years 1987-2015. It was then tested using the same forecast horizon that was used for rice yield forecasting and the resulting forecast errors are: MAE = 5142.95 metric tons, MAPE = 38.07%, and RMSE = 6767.24 metric tons.

Similarly, the same dataset was used to train and test the ARDL model with the only difference of using the time series corn yield data instead of rice paddy yield data as the crop yield variable. The resulting forecast errors are MAE = 3864.268 metric tons, MAPE = 29.53%, and RMSE = 5112.34 metric tons.

Lastly, the FNN model was trained and tested using almost the same dataset with the only difference of using the time series corn yield data instead of rice paddy yield data as crop yield variable. The resulting performance errors are MAE = 481.46 metric tons, MAPE = 4.46%, and RMSE =

481.46 metric tons. Shown below in Table 3 is the tabulated forecast results for the three models.

Table 3: Corn Yield Forecast Results

Model	Performance Metrics		
	MAE (mt)	MAPE (%)	RMSE (mt)
SARIMA	5142.95	38.07	6767.24
ARDL	3864.27	29.53	5112.34
FNN	481.46	4.46	614.468

An observation that can be made is that the forecast performance of all three models has declined compared to their performance in rice yield forecasting. The SARIMA model has seen an about 16% increase in its forecast error, while the ARDL and FNN models have seen an increase of 15% and 0.8%, respectively. The decline in SARIMA and ARDL performance is significant, and one possible reason for this is rice and corn have fundamentally different growth patterns, seasonality, and trends [6]. Because of this, the statistical models may have failed to capture the unique and more complex patterns in the corn yield data, and so the models have poorly predicted future yields. On the other hand, while a slight decline was seen in the performance of the FNN model, its MAPE is still significantly low and is still considered a good result in the context of crop yield prediction [7].

V. Conclusion

With the FNN model performing consistently best in both rice and corn yield forecasting, this reinforces the hypothesis of the researcher that a Neural Network-based forecasting model posits a solution to the decline in the accuracy of classical time series forecasting methods as datasets become more complex. Due to a multitude of contributing factors to crop production like economic shocks, global events, and extreme climatological conditions, accurate crop yield prediction becomes a much more nuanced process as these complexities manifest more in the dataset along with increased dimensionality. At the cost of model interpretability, Neural Network forecasting models can provide good insights into food supply shortages and food security in general. Thus, the researcher urges institutions such as the Philippine Statistics Authority and Department of Agriculture to consider employing machine learning techniques, particularly Neural Networks, to design novel crop yield prediction models. These models not only demonstrate superior robustness and adaptability to abrupt and extreme observations in datasets as shown in section IV.D but are also more straightforward to implement.

Moreover, the researcher reiterates that while the study focuses on the strengths of Neural Networks in dealing with nonlinear and complex data related to agricultural forecasting, the methods used in the study well extend to emerging technologies in communication such as adaptive signal processing and smart sensor networks. By demonstrating the effectiveness of a simple Feedforward Neural Network architecture in recognizing intricate data patterns in a dataset, it lays down the groundwork for exploring the applications of much simpler and easily trainable FNN models for processing real-time, noisy, and nonlinear sensor data that may or may not need adaptive filtering.

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