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Hybrid SARIMA-Facebook Prophet Model for Prediction and Forecasting of the Staple Food Prices in Tanzania

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Abstract: The country's stable development requires sufficient food production and reserves for its people. However, global climatic change and other factors, including political instability, resulted in the shortage and volatility of staple food prices. Thus, the best prediction and forecasting models of staple food prices become essential since the advancement of technology gave room for the development of hybrid models. Therefore, in this paper, we develop the ARIMA/SARIMA-Facebook (FB) Prophet model to predict and forecast staple food prices in Tanzania. Based on the Root Mean Squared Error (RMSE) criterion, the proposed hybrid model outperforms the SARIMA and other models in predicting staple food prices. Moreover, the forecasts for the next two years have shown increasing trends in staple food prices. Since most neighboring countries depend on Tanzania to complement the food crisis in their countries, initiatives should be taken into account to stabilize prices. Finally, the proposed hybrid SARIMA-FB Prophet may be applied to predict and forecast other prices to see the stability of its accuracy. The theoretical model, hybrid SARIMA-FB Prophet, may be constructed in future studies.

Keywords – ARIMA, SARIMA-FB Prophet, Staple food, Time series, RMSE.

AMS subject classification – 90B05, 90B30, 90B50

1. INTRODUCTION

Global growth in food production from 70 percent to 110 percent to meet the demand of the rapid population by 2050 is the fundamental debate. The agricultural sector employment in Africa accounts for 65%, and 61% of rural households depend on agriculture for livelihood in Sub-Saharan Africa (Nijbroek & Andelman, 2016). In Tanzania, the future production of staple food crops remains uncertain due to over-dependence on rainfed, poor agricultural practices, and climate change and variability (Kadigi *et al*.., 2020). Maize experiences higher seasonality compared to rice among staple food crops. The seasonality significantly varies between one market and another. Policymakers should work harder to stabilize food prices and demand seasonality to achieve the Sustainable Development Goal of zero hunger by 2030(Gilbert *et al*.., 2017). The regional markets, rather than global markets, are the source of external pressures on domestic prices. Furthermore, interactions with both external market shocks and domestic weather shocks play a role in how trade policies influence markets (Baffes *et al*.., 2015). Price transmission and spatial price fluctuations for staple foods vary from one place to another as a factor of distance from the markets. The improved roads and market infrastructures may reduce the price fluctuation between producers and wholesale markets across the country (Maziku, 2019). Moreover, direct price incentives resulting from border protection, government involvement in domestic markets, and border price shocks encourage farmers' supply and price fluctuations (Magrini *et al*.., 2018). Climate change potentially makes the communities vulnerable due to decreased agricultural productivity, food insecurity, and water availability (Kangalawe *et al*.., 2017). Supporting market linkage and infrastructure and enforcing transparent and non-restrictive food marketing rules would improve market access (Rajabu *et al*.., 2020). Tanzania experienced various times of food scarcity owing to limited food production. Even though the country has an undeniable food production capacity, the government and development partners must play a more significant role in achieving food self-sufficiency(Mbunda, 2016). Based on policy, climate, and price changes,

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accurate future prediction and forecasting of staple food prices in Tanzania have become important. The Autoregressive Integrated Moving Average(ARIMA) model gains much application in modeling and forecasting the time series data(Box, 1970; Box & Jenkins, 1970). The ARIMA model has got immerse applications in the fields of Business, Economics, meteorology, agriculture, and health, to mention a few. The model still performs well in predicting and forecasting agricultural production(Rahman, 2017; Todri, 2021). The ARIMA and SARIMA models contribute to the market forecasting prices (Boudrioua, 2019; Hussain *et al.*., 2021; Wadi *et al.*., 2018).In the education sector, the enrolment of students has also been predicted using ARIMA and SARIMA models (Chen *et al.*., 2019; Parvez *et al.*., 2021). In the health sector, the ARIMA models have an application in predicting new cases of diseases(Karnaboopathy *et al.*., 2018; Manikandan *et al.*., 2016; Yonar *et al.*., 2020). Using ARIMA and SARIMA models in energy sector prediction is essential in forecasting energy load and demand (Etuk *et al.*., 2016; Pereira *et al.*., 2015). Despite the numerous applications of the Box and Jenkins methodology in recent years, researchers claimed that using individual models in time series forecasting is insufficient. The hybrid time series models have caught much attention and have excellent performance (Khashei & Bijari, 2012).

Therefore, this paper is divided into five sections. Section two discusses related literature on hybrid models and proposes a suitable hybrid model for predicting and forecasting staple food prices; Section three describes the material and hybrid methodologies for the study. Section four will discuss the results obtained. Finally, section five will provide a conclusion and recommendations for further studies.

2. RELATED LITERATURE

Technology and advanced computer knowledge have brought changes in modeling and algorithm development. Several pieces of literature talk about the hybrid time series models. The hybrid ARIMA–ANN model outperforms individual models in the time series multi-step ahead forecasts with the highest accuracy (Babu & Reddy, 2014). The comparison model on the generated values of the observed data showed that the wavelet-SARIMA-ANN model outperformed the wavelet-ANN and wavelet-SARIMA models in terms of forecasting accuracy(Shafaei *et al.*., 2016). The comparative performance analysis of the proposed methodology with ARIMA, ETS, the Multilayer Perceptron(MLP), and some existing hybrid ARIMA–ANN models shows that the proposed hybrid model statistically gave optimistic predictions results (Panigrahi & Behera, 2017). The hybrid methodology that integrates empirical mode decomposition (EMD) and the ARIMA model applied to forecasting the monthly rice prices in Malaysia has increased the accuracy (Abadan & Shabri, 2014). Experimental results with real data sets indicate that the combined model can effectively improve forecasting accuracy instead of using models separately (Zhang, 2003). A hybrid model was proposed incorporating ensemble empirical mode decomposition (EEMD), ARIMA, and Taylor expansion with a tracking differentiator. The EEMD decomposes the financial time series into subseries. The ARIMA and Taylor expansion models forecast the linear and non-linear portions. The real financial time series data findings revealed that the hybrid model outperforms the benchmark models (Luo *et al.*., 2021). The combination of ANN and ARIMA in forecasting the future exchange prices for US Dollar (USD) / Indian Rupees (INR) reveals that the hybrid ANN-ARIMA can closely forecast the foreign exchange rates (Priyadarshini *et al.*., 2020). A hybridization methodology based on integrating the SARIMA and ANN models to predict the number of inspections indicates that the hybrid SARIMA-ANN model outperforms individual models(Ruiz-Aguilar *et al.*., 2014). The hybrid SARIMA model that integrates Support Vector Regression (SVR)with Gaussian white noise applied to forecast the future statistical indicators in the aviation industry was proposed. The results of the empirical study suggest that the proposed hybrid SARIMA-SVR increases forecasting accuracy (Xu *et al.*., 2019). Furthermore, the hybrid ARIMA–ANN model to forecast electricity prices improved prediction accuracy (Babu & Sure, 2016). Based on the literature review, the proposed hybrid model works better than individual models.

Therefore, a hybrid model can effectively improve the forecasting accuracy of traditional methods using appropriate strategies. In this paper, we will combine ARIMA or SARIMA model and the FB Prophet models and apply the best hybrid model in forecasting the staple food prices in Tanzania. Furthermore, the proposed hybrid model will be compared with the individual and hybrid machine learning models.

3. MATERIALS AND METHODS

3.1 Data specification

This paper considers monthly recorded data of the staple food prices collected from the Ministry of Industry and Trade, the government of the United Republic of Tanzania. The data covers the time between January 2005 and December

2021. The analysis of the two datasets is important due to climate change, war, outbreaks of pests and diseases, and the global Coronavirus pandemic, which affects global food production and, ultimately, hunger. The data was divided into 80% and 20% training and testing sets.

3.2 Prediction models

3.2.1 Autoregressive Integrated Moving Average Model (ARIMA) Model

The Autoregressive Moving Average (ARMA) model is the combination of the Autoregressive (AR) and Moving Average (MA) Models(Box, 1970; Box & Jenkins, 1970). The autoregressive model predicts the current value based on the previous observations $w_{t-1}, w_{t-2}, ..., w_{t-p}$, while the Moving Average model predicts the current value using the residuals of the previous values $\varepsilon_{t-1}, \varepsilon_{t-2}, ..., \varepsilon_{t-p}$.

The AR model of order p is given by:

$$w_t = \psi_1 w_{t-1} + \psi_2 w_{t-2} + ... + \psi_p w_{t-p} + \varepsilon_t \tag{1}$$

The model in Eqn. (1) can be re-written as:

$$w_t - \psi_1 w_{t-1} - \psi_2 w_{t-2} - ... - \psi_p w_{t-p} = \varepsilon_t \tag{2}$$

By applying the backward shift operator $B^j w_t = w_{t-j} \{j = 1, 2, 3, ..., p\}$, the model in Eqn. (2) can be re-written as:

$$\psi(B) w_t = \varepsilon_t \tag{3}$$

The MA model of order q is given by:

$$w_t = \varepsilon_t + \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + ... + \phi_q \varepsilon_{t-q} \tag{4}$$

By applying the backward shift operator $B^j \varepsilon_t = \varepsilon_{t-j} \{j = 1, 2, 3, ..., q\}$, the model in Eqn. (4) can be re-written as: -

$$w_t = \phi(B) \varepsilon_t \tag{5}$$

The model is used for forecasting a stationary time series, and it's given in Eqn. (7).

$$w_t = \psi_1 w_{t-1} + \psi_2 w_{t-2} + ... + \psi_p w_{t-p} + \varepsilon_t + \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + ... + \phi_q \varepsilon_{t-q} \tag{6}$$

Now, supposed $w_t \sim I(d)$ is the stationary series after d^{th} the order of differencing, we say $z_t = (1-B)^d w_t$, and can be written as:

$$(1-B)^d w_t = z_t = \psi_1 z_{t-1} + \psi_2 z_{t-2} + ... + \psi_p z_{t-p} + \varepsilon_t + \phi_1 \varepsilon_{t-1} + \phi_2 \varepsilon_{t-2} + ... + \phi_q \varepsilon_{t-q} \tag{7}$$

We are introducing the backward shift operator, Eqn. (7) can be written as:

$$\psi(B)[1-B]^d w_t = \phi_1(B) \varepsilon_t \tag{8}$$

The above-postulated model in Eqn. (8) works only when there is no seasonal variation. If the variable contains a seasonal component, then it is called Seasonal ARIMA or SARIMA model. The seasonal ARIMA model incorporates both non-seasonal and seasonal components in a multiplicative model. The $SARIMA(p,d,q)*(P,D,Q)_S$ model is given by:

$$\psi(B)\Psi(B^S)(1-B)^d(1-B^S)^D w_t = \phi(B)\Phi(B^S)\varepsilon_t \tag{9}$$

Where, Ψ and ψ are the AR parameters for the seasonal and non-seasonal components, respectively, while Φ are ϕ the MA parameters for the seasonal and non-seasonal components, respectively, B is the backward operator, D and d are the differencing terms.

In fitting the ARIMA/SARIMA models, it involves three main stages.

a) Model identification: This stage involves the analysis of autocorrelations, partial autocorrelations, and cross-correlations. To assess if differencing is required, stationarity tests are done.
b) Model estimation and diagnostic tests: The model's appropriateness is determined using diagnostic statistics generated by the estimate. The white noise residual tests determine whether the residual series has additional information that a more complex model might use.
c) Forecasting: We forecast the future values of the time series and generate confidence intervals for these forecasts.

3.2.2 Facebook FB Prophet Model

The FB Prophet is a developed time series prediction model that is simple and practical without much data preprocessing(Taylor & Letham, 2018). The FB Prophet model can quickly fit and automatically fill in the missing values. Furthermore, the FB Prophet model allows for flexible adjustment of periodicity, making it suited for various applications. The FB Prophet time series forecasting model comprises trend, cyclic, festival, and error items. The model's composition is as follows:

$$y(t) = g(t) + s(t) + h(t) + e(t)$$

Where, $g(t)$ is the trend function, $s(t)$ is the periodic term function, $h(t)$ is the impact from the holidays, and the $e(t)$ is the error term.

Where:

i) The $g(t)$ can either take the form of the logistic growth model or the piece-wise regression model as follows: -

a) For the logistics growth model, $g(t) = \frac{c}{1 + e^{(-k(t-m))}}$, C is the saturation value, k is the growth rate, and m is the bias parameter.

b) For the piece-wise regression, $y = \begin{cases} \beta_0 + \beta_1 x & x \le c \\ \beta_0 - \beta_2 c + (\beta_1 + \beta_2)x & x > c \end{cases}$, where c is the trend changepoint.

ii) The periodic term function $s(t)$ is based on the Fourier series, which results in periodic effects on model flexibility (Harvey & Shephard, 1993). With a conventional Fourier series, the approximate arbitrary smooth seasonal effects are as follows:

$s(t) = \sum_{n=1}^{N} \left[a_n \cos\left(\frac{2\pi nt}{P}\right) + b_n \sin\left(\frac{2\pi nt}{P}\right) \right]$, t represent periods and P is the regular periodic length of the time series; it can be daily, monthly, or yearly.

iii) The impacts from the holidays, $h(t) = Z(t)\mathrm{K}_i$; $\mathrm{K}_i \sim N(0,\sigma)$, $Z(t) = [\mathrm{I}(t \subset D_1),...,\mathrm{I}(t \subset D_i),....,\mathrm{I}(t \subset D_L)]$, **I** represents holidays; *D* represents the collection of past and future holidays; **K** represents the impact of each holiday on the forecast.

3.2.3 Hybrid SARIMA-FB Prophet Model.

Suppose $\{Y_t,\ t = 1,2,3,...,N\}$ has two parts, $\{SARIMA_t,\ t = 1,2,3,...,N\}$ which represent the linear SARIMA model and $\{FB_t,\ t = 1,2,3,...,N\}$ which represent non-linear FB Prophet model, as presented in Eqn. (11).

$$Y_t = SARIMA_t + FB_t \tag{10}$$

Where S_t and FB_t denotes the linear and non-linear components, respectively. First, the linear part is obtained by fitting the best SARIMA model. Then, the non-linear part is derived from the best-fitted linear model, and then we extract the residuals to fit the hybrid SARIMA-FB Prophet model. Finally, the residual of the best model is given in Eqn. (12).

$$e_t = Y_t - SARIM\hat{A}_t \tag{11}$$

Then, the extracted SARIMA model for residual with g input nodes is given in Eqn. (13).

$$e_t = f(e_{t-1}, e_{t-2}, ..., e_{t-n}) + \varepsilon_t \tag{12}$$

Finally, we can find $\hat{Y}_t$ (The final forecasted result of the hybrid SARIMA-FB Prophet model) given in Eqn. (14).

$$\hat{Y}_t = SARIM\hat{A}_t + F\hat{B}_t \tag{13}$$

3.2.4 Performance Metrics

To determine the best model, the Mean Absolute Percentage Error (MAPE) and the Root Mean Squared Error (RMSE) Error criterion were applied to measure model prediction accuracy. The MAPE and RMSE measure the differences between actual and predicted values(Hodson, 2022). Then, Eqn. (15) and (15) are the MAPE and RMSE formulas.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \tag{14}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_t - \hat{y}_t\right)^2} \tag{15}$$

Where the y_t is the actual value, $\hat{y}_t$ is the forecasted value, and n is the forecasting horizon.

4. Empirical Results and Discussion

4.1 The plot of the Staple food prices from 2005 to 2021

The prices of beans and rice have increased compared to other staple food. The round potatoes, maize, and sorghum prices are low for the recording duration. This shows that rice and beans are the most preferred food; thus, their demand increases their prices. Even though Tanzania has been suffering from a food deficit for decades, a robust agricultural policy is required to stabilize agricultural production and prices (Mkonda & He, 2017). Institutional and policy-induced factors influence farmers' decisions on which market to sell their primary goods. As a result, there is a lack of motivation to participate in the production and commercialization of agricultural commodities. These factors influence farmers' decisions on which basic food market to buy in Tanzania. Farmers' integration into staple food markets is poor; according to the findings, female-headed households face more challenges(Kangile *et al.*., 2020). Fig. 1 shows the staple food prices in Tanzania from 2005 to 2021.

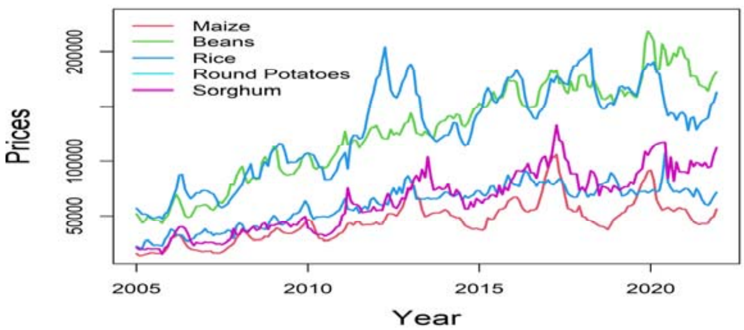

Figure 1: Plot of the Staple Food Prices in Tanzania

4.2 Descriptive Statistics of Staple Food in Tanzania.

Descriptive statistics show that rice and beans have recorded higher prices among the five staples food prices than the rest. Tanzania has a zonal-based production of these crops; rice is produced high in the lake zones and southern part of Tanzania. At the same time, beans are in the northern and southern regions. Climate change may affect production; thus, if the demand is high, it may lead to shortages and eventually shooting prices. In addition, the global issues in the areas in which oil production is taking place may also increase staple food prices due to the increase of crude oil per barrel. Table 1 below shows the summary statistics of staple food prices.

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Table 1: Summary Statistics

Variables	N	mean	sd	median	min	max	skewness	kurtosis	Q0.25	Q0.75
Maize	204	45663.45	18598.3	44213.7	14298	106166.4	0.645635	0.694675	33415.71	56000.05
Potatoes	204	60733.59	18373.92	66710.85	20950	107448.8	-0.46889	-0.77442	46690.09	73232.55
Rice	204	128696.2	42166.44	136008.3	47654	204025.4	-0.27714	-1.07227	95458.35	163326.7
Beans	204	128399.3	45028.58	132272.4	43557	219078.9	-0.25725	-0.9483	94324	164788.3
Sorghum	204	64789.2	27960.09	66341.97	15801	132964.9	0.078813	-1.04384	39032.93	88872.58

Table 2: Proposed model summary

Variable	Model	RMSE	MAE	MAPE	Ranking of RMSE
Beans	FB Prophet	16224.10	13824.22	7.44	1
	SARIMA	31418.28	25847.75	13.39	2
	SARIMA-FB Prophet	31525.54	26278.86	13.66	3
Maize	FB Prophet	17565.67	15935.69	29.63	3
	ARIMA	15524.80	10609.04	16.52	2
	ARIMA-FB Prophet	15384.90	10573.17	16.43	1
Rice	FB Prophet	37831.31	31965.75	22.02	3
	SARIMA	17600.33	15530.32	9.89	2
	SARIMA-FB Prophet	17489.06	15650.63	9.94	1
Round Potatoes	FB Prophet	12637.03	11343.99	15.94	1
	SARIMA	31418.28	25847.75	13.39	3
	SARIMA-FB Prophet	26840.80	25138.17	35.63	2
Sorghum	FB Prophet	15634.96	13695.09	15.49	1
	ARIMA	17600.33	15530.32	9.89	3
	ARIMA-FB Prophet	16188.37	12513.40	12.07	2

4.4 The comparison between the developed hybrid and other machine learning models.

Using the R software, the proposed hybrid ARIMA/SARIMA-FB Prophet is ranked 5, 2, 2, 3, and 3 in predicting the prices of beans, maize, rice, round potatoes, and sorghum, respectively. In this case, the proposed ARIMA/SARIMA-FB Prophet model performed better for predicting maize and rice prices based on the RMSE criterion. The ELM model is ranked first in the prediction of beans and round potatoes, SARIMA-MLP is ranked first in the prediction of rice, and the MLP model is ranked first in the prediction of maize and sorghum. The proposed hybrid model continues to perform better than other predictive models, although in some cases, the individual models outperform hybrid models depending on the scenario. Therefore, the prediction of the prices of staple food is still difficult since each type of food uses a different model. Table 3 shows the summary of the proposed hybrid model against the machine learning models.

4.5 The best model forecast of the staple food prices in Tanzania.

The forecast of the staple's food prices is based on the models' overall performance, as indicated in Tables 2 and 3. The next 2 years' forecasts from the four staple food prices are shown in Fig. 2, 3, 4, 5, and 6. The forecast from the best models from December 2021 to December 2024 shows an increase in prices for staple food prices in Tanzania. The forecast alerts the government and other policymakers to take the initiative to stabilize the prices by combating climate change and reducing the tax on equipment and other related production facilities. The ongoing war in the oil-producing countries has already impacted the agricultural sector in different ways, such as increased cost of running production machinery and transportation of the harvest from farm to the consumers. Fig. 2,3,4,5, and 6 show the next 2 years' forecasts from the best models for beans, maize, rice, round potatoes, and sorghum.

Table 3: Proposed model Vs Machine learning models

Variables	Model	RMSE	MAE	MAPE	Ranking of RMSE
Beans	SARIMA-FB Prophet	31525.54	26278.86	13.66	5
	MLP	27543.08	22194.45	11.54	2
	ELM	27072.25	21018.99	10.81	1
	SARIMA-MLP	30725.68	25345.83	13.14	3
	SARIMA-ELM	31028.07	25422.16	13.15	4
Maize	SARIMA-FB Prophet	15384.90	10573.17	16.43	2
	MLP	13550.12	10395.35	17.84	1
	ELM	16459.24	11749.06	17.58	5
	SARIMA-MLP	15480.27	10591.57	16.53	4
	SARIMA-ELM	15028.45	10419.65	16.60	3
Rice	SARIMA-FB Prophet	17489.06	15650.63	9.94	2
	MLP	22529.09	18395.65	11.14	5
	ELM	21423.02	19486.97	12.66	4
	SARIMA-MLP	17441.12	15635.43	9.99	1
	SARIMA-ELM	18357.03	15692.01	9.69	3
Potatoes	SARIMA-FB Prophet	26840.80	25138.17	35.63	3
	MLP	22380.47	20732.71	29.36	2
	ELM	22826.42	21485.08	30.44	1
	SARIMA-MLP	27247.41	25531.13	36.18	5
	SARIMA-ELM	27057.56	25473.02	36.09	4
Sorghum	SARIMA-FB Prophet	16188.37	12513.40	12.07	3
	MLP	12656.46	9600.99	9.44	1
	ELM	16903.55	12946.46	12.38	5
	SARIMA-MLP	16390.57	12420.54	11.87	4
	SARIMA-ELM	14333.61	10821.17	10.52	2

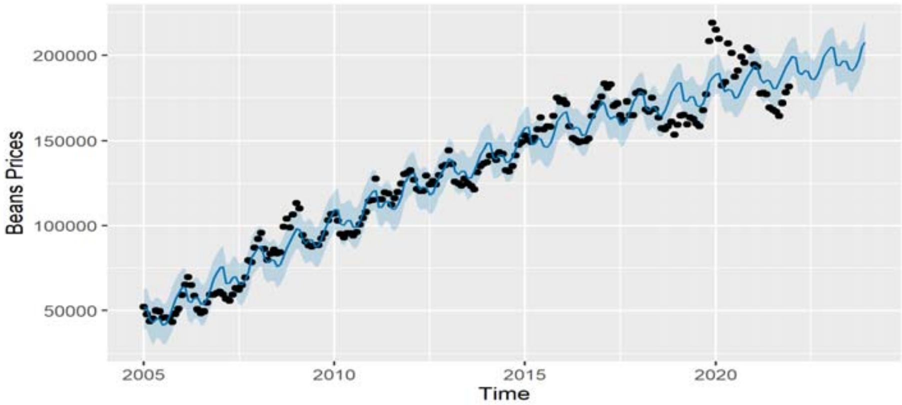

Figure 2: 2 Years of beans prices forecast using FB Prophet model.

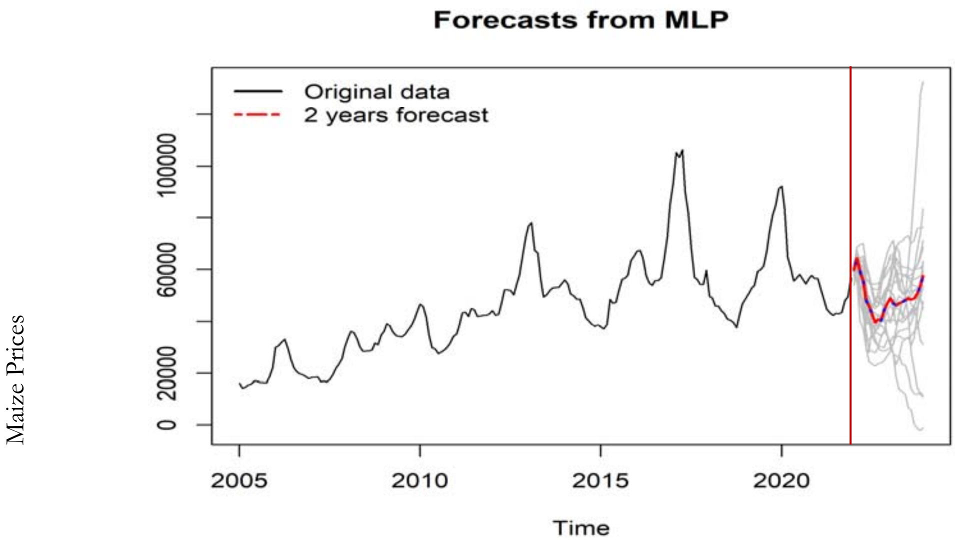

Figure 3: 2 Year's maize prices forecast using MLP model.

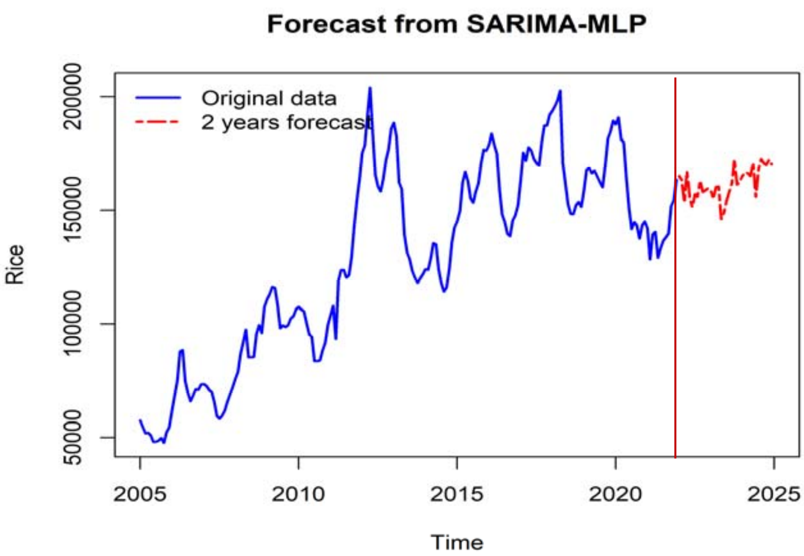

Figure 4: 2 Year's rice prices forecast using the SARIMA-MLP model.

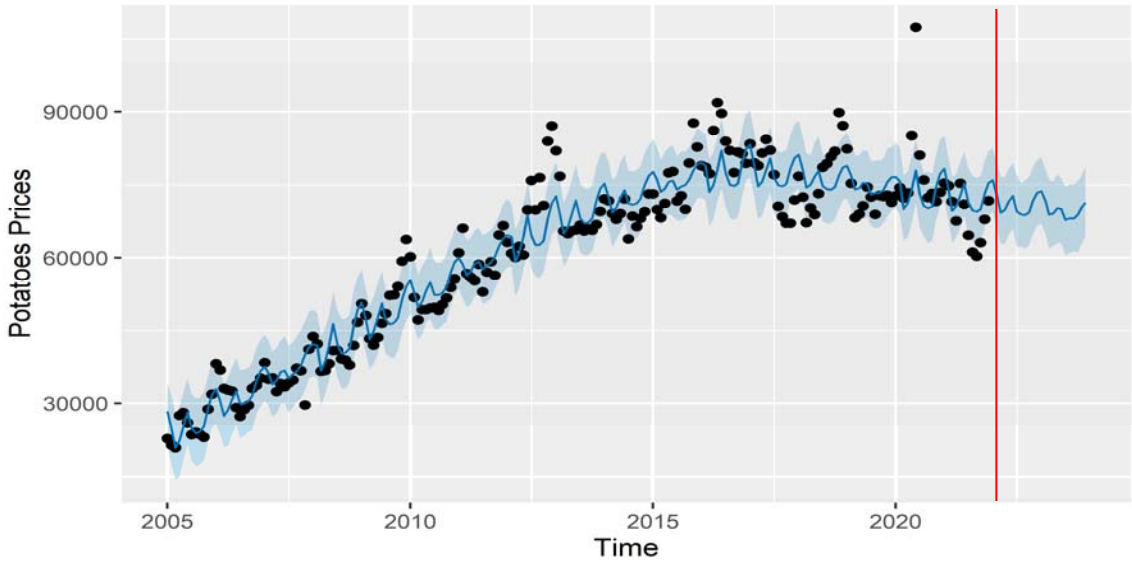

Figure 5: 2 Years round potatoes prices forecast using FB Prophet model.

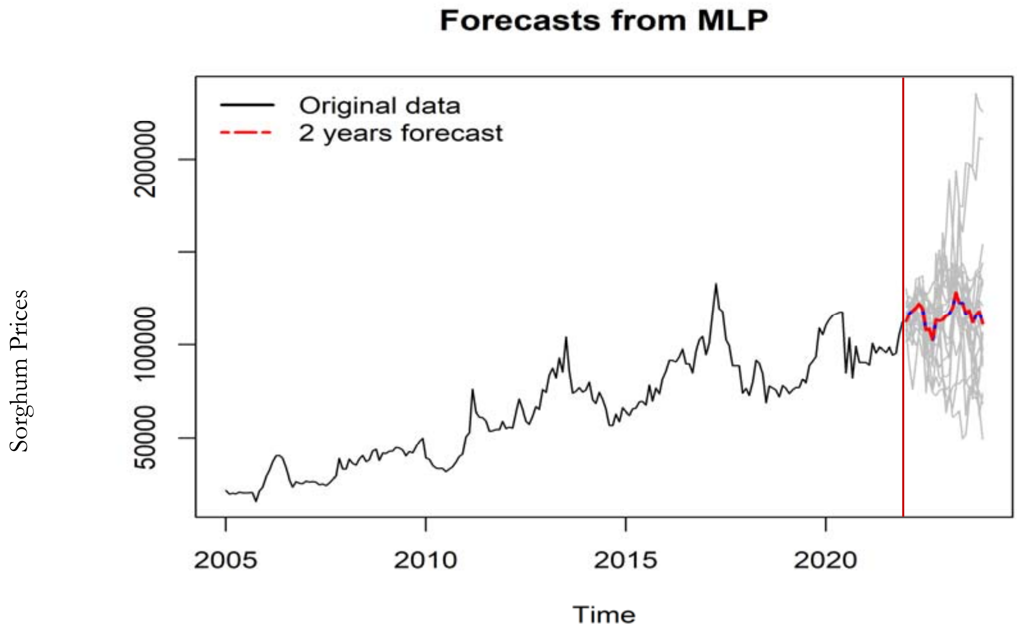

Figure 6: 2 Years sorghum prices forecast using MLP model.

5. CONCLUSION

The hybrid SARIMA-FB Prophet model has shown a more significant performance than the individual ARIMA/SARIMA model based on the RMSE criterion. The proposed model has shown a convincing performance except in predicting the maize price. Thus, the researchers may use the model to predict other prices. Compared with individual models, the SARIMA-FB Prophet model can effectively improve an individual model's prediction and forecasting accuracy. The comparison between the hybrid ARIMA/SARIMA-FB Prophet and machine learning models shows that the model still performs better, although the individual ML model performed well in some prediction cases. The next two years' forecast of staple food prices using the best-selected model shows an increase in prices. Therefore, private and government planners may formulate more scientific replenishment planning to assure the country's food security and price stability. In this paper, only the hybrid SARIMA-FB Prophet model is developed; other hybrid models may be designed in the future for further improvement of the prediction and forecasting accuracy.

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