An Econometric Model-Based Projection of Nigeria's Rice Self-Sufficiency

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Abstract

Inspired by Nigeria's unrelenting pursuit for self-sufficiency in rice, this paper projects Nigeria's rice self-sufficiency levels which could facilitate policy directives on areas in the country's rice market that show potentials needed for to achieve its goal through improved planning decisions. Using time series data covering the period from 1980 to 2018, this study adopted an econometric technique to model Nigeria's rice market which was estimated using a dynamic Autoregressive Distributed Lag (ARDL) approach. The results revealed that paddy producer price elasticity was 0.206 and had no influence on paddy area harvested. On the other hand, the national policy of rice credit guarantee scheme variable displayed a positive relationship with paddy area harvested. Lagged yield and lagged area harvested had positive influences on yield and area harvested, respectively. This could mean that paddy producers were motivated by previous year's yield levels and area harvested. The demand own-price elasticity of rice was -0.321 and its cross-price elasticity was 0.193, with wheat revealed to be a substitute. The obtained elasticities were then used to make a ten-year projection. Results suggested that by 2028, increasing rice production relative to dwindling imports will boost rice self-sufficiency level to 71%. However, the average yearly rice self-sufficiency level was 53%, requiring 3.85 million Mt of rice imports. The projections revealed that Nigeria will not achieve rice self-sufficiency by 2028 unless intensive yield enhancing policy-supporting efforts are pursued.

Keywords: rice, self-sufficiency, Autoregressive Distributed Lag, elasticities, projection

Introduction

In Nigeria, annual rice consumption per capita is estimated at 33.35 kg (FAOSTAT, 2023), making it an important national staple. With a growth rate of 5.3% between 2007 and 2018, the country's regional consumption was estimated to be 20.74% of Sub-Sahara (PS&D Online database). Within the same decade, the country's rice supply was estimated at 8735 thousand Mt (USDA, 2019). This figure included import volumes of 2133 000 Mt (24%) as the country is incapable of satisfying the demand with domestic supply, which has costed it huge import bills over the years. According to Klynveld Peat Marwick Goerdeler (KPMG) (2019), Nigeria spends approximately US$5 million daily on rice imports which is expected to increase because the rice outlook for the 2019–2028 period, shows rice imports are expected to reach 5274.73 thousand Mt, and world rice prices are expected to increase by 5.15% to US$470 Mt^{-1} by 2028 from 2018 (OECD/FAO, 2019). These unfavourable import dependence and bleak forecast incited a renewed policy directive of pursuing self-sufficiency in rice since 2005 and have been fostered by various government regimes at both federal and state levels. Although the country is endowed with a significant yield potential of 9Mt ha^{-1}, for irrigated paddy (Global Yield Gap Atlas Online database, 2020), a current yield of two Mt ha^{-1} which contributes to producing an average of 2.5 million Mt of rice is insufficient to feed its growing population as indicated by a rice self-sufficiency level (SSL) of 64% in 2018. Several factors have been reported as being responsible for the supply-demand imbalance. On the demand side, factors like population growth, increasing incomes and urbanisation (Onu, 2018) have been pushing the demand for rice, with projections revealing that by 2029, an estimated 267.5 million people in Nigeria will need 9.3 million Mt of rice (PS&D Online database). Therefore, feeding these people will require intensive efforts by all stakeholders in the country's rice sub-sector. On the part of the federal government and facilitated by various institutions, organisations and projects, huge investments in rice self-sufficiency supporting projects/programmes numbering at least 15 since 2005 have been pursued. The latest of which are the Agricultural Transformation Agenda (2011 to 2015), the Agricultural Promotion Policy (2016 to 2020) and the National Rice Development Strategy - phase II which was initiated in 2020 with the aim of surpassing self-sufficiency in rice by the year 2030. Nevertheless, the self-sufficiency level of 64% in 2018 puts the successes of these projects/programmes into question. More so, historical data as presented in Figure 1 show an inconsistent trend in rice SSL. Udemezue (2018) attributed the failure of some of these programs to managerial and infrastructural failures, instability of policy implementation resulting from frequent changes in governments. These factors lead to high cost of agricultural inputs which were unaffordable to farmers (Udemezue,, 2018). Nevertheless, there seem to be some progress stemming from some of these programs. Recent production data has reported substantial growth in rice production data for 2016 show a 15% growth in paddy production from 2015. However, this growth is still unable to have any significant effect on rice SSLs (Figure 1).

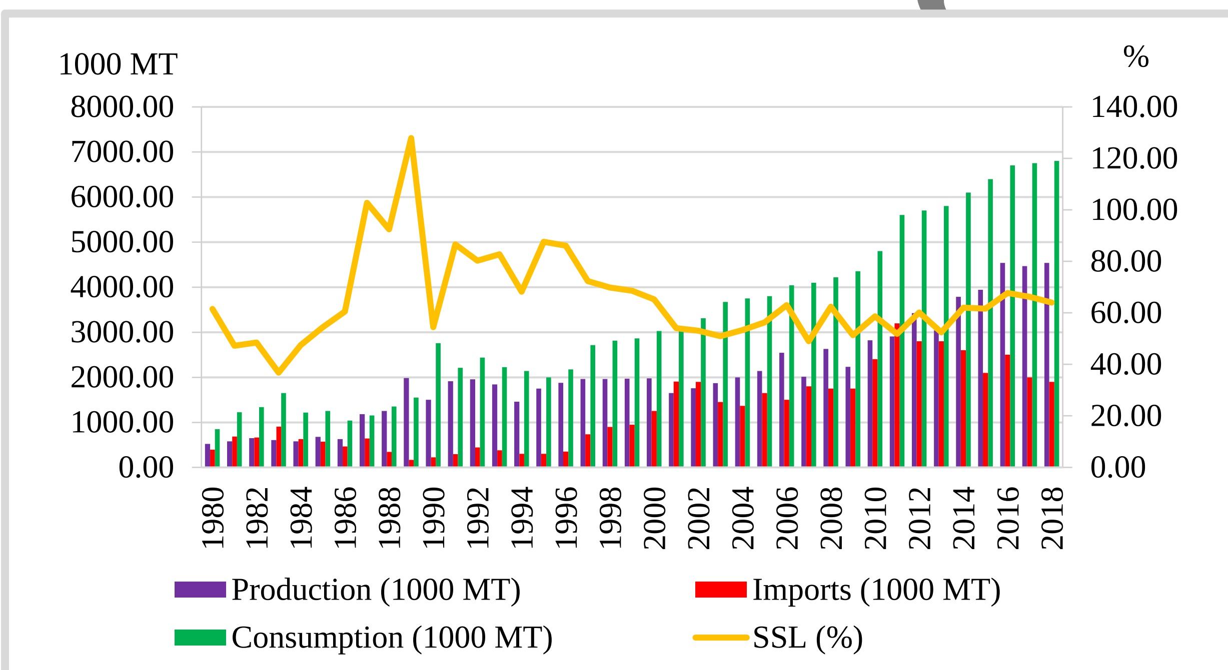

Figure 1. Trends in key rice self-sufficiency variables in Nigeria
Source: PS&D Online Database

The consistency and relentless efforts of the Federal Government of Nigeria in its rice sub-sector over the years bears testament to its commitment to achieving the goal of self-sufficiency. Under the existing circumstances, the inability of the country to achieve its policy goal of self-sufficiency in rice might be related to a lack of information supported by empirical evidence on the capability of the country to reach self-sufficiency in rice in the first place. As supported by Kholikova (2020), such information is considered a key factor in the successful development of an enterprise/industry (Kholikova, 2020). Therefore, the importance of projection/forecasting to Nigeria’s agri-food sub-sector needs little motivation. The accuracy and consistency of supply and demand forecasts are unquestionably critical for effective planning in agri-food markets, and this is also true for Nigeria's rice industry. Agricultural policy analysts have benefited from considerable advances in forecasting/projection over the past decades. With particular reference to agricultural commodity markets, forecasting serves to not only provide relevant information on agricultural commodities in advance, which decision-makers rely on but also reduces uncertainties and risks in agricultural markets (Wang, Yue, & Wei, 2017). Reliable information on certain variables of commodity markets is crucial for decision-makers. For example, while price forecasts have a significant influence on decision-making, and by extension, on resource allocation and economic welfare (Colino & Irwin, 2010), to the government, such market information guides consumer interests to plan for their activities and initiatives (Kumar et al., 2020). Furthermore, macro perspective, forecasting provides the basis for making appropriate decisions regarding the adaptation of appropriate regulations for agricultural markets or the shaping of agricultural policy (Zielinska-Sitkiewicz & Chrzanowska, 2018).

The food self-sufficiency (FSS) agenda adopted by many countries has inspired a large collection of studies on the topic, focusing on a variety of different aspects among which is forecasting. The foundation of forecasting theory is the idea that predictions can be made using both historical and current data (Petropoulos et al., 2022). Recent developments in forecasting, geared towards distinct aims, have produced a range of forecasting methodologies to address real-life challenges, propelling the field of forecasting towards amazing growth in both theory and practice. However, in the field of FSS, empirical evidence on its forecasting is quite limited, which could result in substantial uncertainties in this aspect. One reason for this is probably because the concept of FSS is broad and comprises multiple inter-related variables. Hence, for simplicity purposes, a literature search on forecasting approaches in the topic of FSS broadly categorise the commonly applied methods into times series and econometric/statistical.

In cases where research interests centre on simple and short-term forecasting, the time series method particularly Auto Regressive Integrated Moving Average (ARIMA) models are considered suitable. The ARIMA algorithm applies to data with high and stable correlation (Weng et al., 2019) and they are quite robust and not as prone to the problem of overfitting as more complex methods. This method proved reliable in the works of Ardie et al. (2021) and Samim et al. (2021) who forecasted SSLs for corn and other grains, respectively. However, such simple forecasts may be inadequate, especially for policy formulation purposes. The reality is that in the analysis of forecasting, certain situations might present the need to investigate other relevant factors like policies or climate change that might contribute to fluctuations in the variable under consideration. This ability to examine the influence of related factors is not accommodated by ARIMA (Mustafa & Ünal, 2017; Xu 2017; Xu 2018).

Studies adopting econometric or statistical methods, such as regression, vector autoregressive model and ARDL, are motivated by interests in predicting self-sufficiency while considering influencing factors like levels of input use, climate change and policies. This is due to the econometric approach's ability to simulate how different sectors' elasticities and aggregates' responses will react to changes in the explicative variables (Monasterolo et al., 2015). For example, using a single econometric model, Kurnia and Iskandar, (2019) in their study, identified factors influencing future FSS in Indonesia. Similarly, Hudoyo et al. (2016) employed a two-equation regression model of demand and supply to forecast that Indonesia will achieve self-sufficiency in rice by 2028 and established area harvested, seeds and population as influencing factors. Adopting a slightly different approach, Seng et al. (2017) adopted an econometric market model which are credited to explaining market behaviour (Labys, 2003) to forecast rice SSF for Sabah, Malaysia. Their analysis forecasted the rice SSL of Sabah at 38% due to limited land use for paddy cultivation (Seng et al., 2017). Beyond the analytics of the problem being studied, the econometric approach is important because it can be used to model the business processes of economic sectors, develop models that can control and forecast these processes in terms of quantity and quality, and offer guidance for management decisions or advisory proposals based on research for the successful management of the object under study (Rakhmatullaevna, 2021). When applied to food SSL studies, econometric methods can provide its prediction while considering influencing factors like levels of input use, climate change and policies. However, the approach presents relevant limitations which may reduce the representativeness of results because results from such models are sensitive to the structure and specification of the model (Monasterolo et al., 2015).

The review show that researchers have achieved appreciable progress in the techniques/methods applied to forecasting FSS. It highlights the need to tailor techniques to the research objective under consideration using models ranging from simple to fairly complex models, with these methods delivering interesting insights. Nevertheless, the ultimately gain is in achieving the crucial task of forecasting FSS goals and understanding its dynamics in consideration of other related variables. Hence, the econometric approach is a useful tools for guiding policy design that could help create efficient agricultural food market systems and promote sustainable economic development.

The need for this study was substantiated by the argument that projecting the country's rice self-sufficiency level and its associated parameters serves in understanding the dynamics of the country's rice market which could facilitate national policy formulations and to a larger extent, serve as a toolkit to develop or improve regional competitiveness. Hence, a key question is whether Nigeria can be self-sufficient in rice given its current market environment. In this regard, this study sought to forecast Nigeria's rice SSL using an econometric approach.

Methodology

Data Source

The dataset for this study spanned 38 years, from 1980 to 2018. Data were sourced from various databases. Specifically, data on paddy/rice production, consumption and population were obtained from the International Rice Research Institute (IRRI) online database, retail prices of rice and wheat were obtained from sources such as FAO'S GIEWS online database, various issues of Nigeria's National Bureau of Statistics Annual abstract of statistic and various issues of Central Bank of Nigeria's statistical bulletin, paddy producer price were sourced from FAO's FAOSTAT online database, data on Gross National Income per Capita was retrieved from Central Bank of Nigeria database, and Nigeria's currency exchange rate, as well as the world price of rice, were retrieved from UN Comtrade online database.

Conceptual Framework of Nigeria's Rice Model

This study adopts a commodity market approach based on the concepts proposed by Labys (1973). A commodity model is a quantitative representation of a commodity market or industry in which the behavioural relationship included reflects demand and supply aspects of price determination as well as other related economic, political and social phenomena (Labys. 1988). According to Labys (2003), a simple commodity market model for a non-storable product is a multi-equation market equilibrium formulation consisting of three main components - demand, supply, and price. Conceptually, the market equilibrium is determined by demand and supply. As this market model approach relates to a single economic sector (Labys, 2003), it lends itself well to FSS analysis. Therefore, drawing inspiration from the conceptual framework established by Labys (1973) with modifications by Shamsudin (2008), the Nigeria rice market was modelled, based on available data. The model, depicted in Figure 2 comprised of the demand, the supply and the price components. The rice market price was determined based on the market clearing condition which equates the total supply of rice to its total demand. By creating a link between the price of rice at retail and the price of the paddy producer, the price linkage component helped to combine the supply and demand elements into a single model. It is, therefore, a small partial equilibrium model that takes into account the fundamental variables of supply, demand, price, and policy in the nation's rice market.

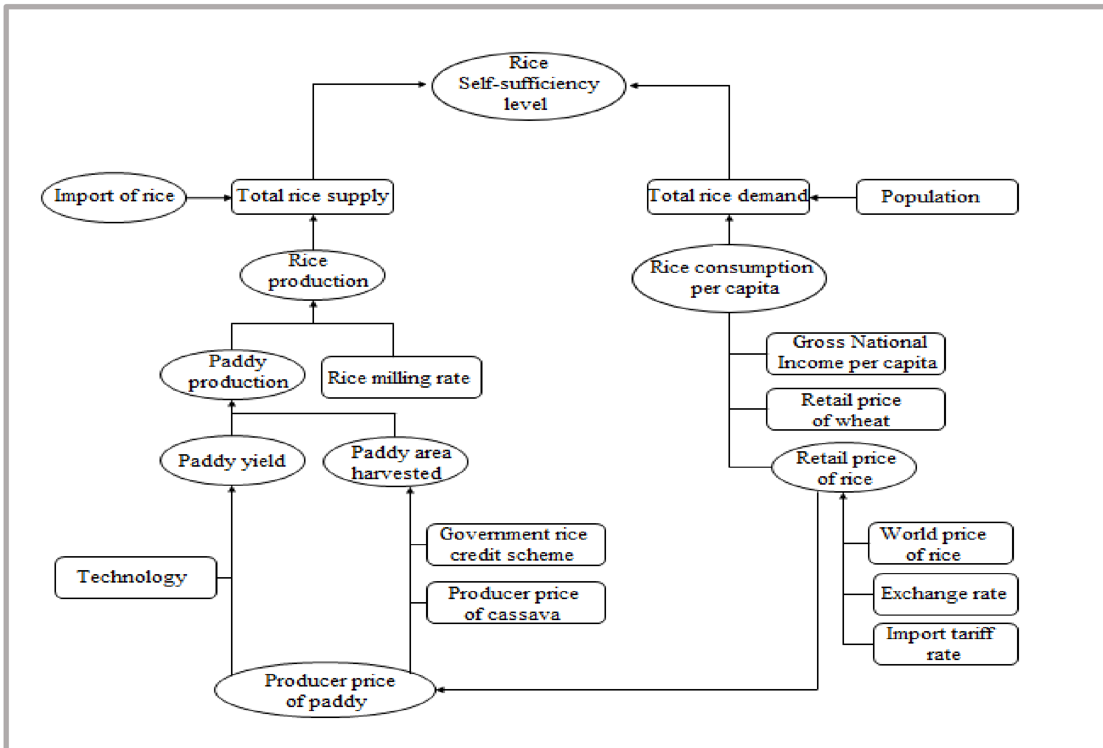

Figure 2: Conceptual framework of Nigeria's rice market

The Econometric Model

Following FAO's definition, the country's rice self-sufficiency is calculated as the ratio (in percentage) of domestic rice production to domestic rice demand. This concept of FSS set the pathway for the analysis process which began with a specification and subsequent estimation of a dynamic econometric model for Nigeria's rice market. The model consisted of four structural equations representing paddy area harvested, paddy yield, paddy producer price and rice consumption per capita, and five identities for paddy production, rice production, rice import, rice retail price and rice SSL. The model structure is presented in Table 1.

Table 1: The Nigeria's Rice Market Model Specification

S/N0	**Equation**
Supply	
[1]	$PYAH_t = f(PYAH_{t-1}, PYPP_{t-1}, CVPP_{t-1}, CGSF_{t-1})$

[2]	$PYYD_t = f(PYYD_{t-1}, PYPP_{t-1}, TREND_t)$
[3]	$PYPN_t = PYYD_t * \mathrm{PYAH}_t$
[4]	$REPN_t = PYPN_t * PYMR_t$
[5]	$REIM_t = \mathrm{NTRD}_t - \mathrm{REPN}_t$
Demand	
[6]	$REPC_t = f(REPC_{t-1}, RERP_t, WTRP_t, GNIPC_t)$
[7]	$\mathrm{NTRD}_t = \mathrm{REPC}_t * \mathrm{POP}_t$
Price	
[8]	$\mathrm{RERP}_t = [\mathrm{REWP}_t\ (1 + \mathrm{REIT})] * \mathrm{EXRT}_t$
[9]	$\mathrm{PYPP}_t = (\mathrm{PYPP}_{t-1}, \mathrm{RERP}_t)$
SSL	
[10]	REPN x 100 / (REPN + REIM)

Definitions of Variables

PYAH_t – Paddy Area Harvested in Hectares
PYYD_t – Paddy Yield in Mt ha^{1}
PYPN_t – Paddy Production in Mt
REPN_t – Rice Production in Mt
PYPP_t – Paddy Producer Price in ₦ Mt^{-1}
CVPP_{t-1} – Cassava Producer Price in ₦ M^{-1}
GCSF_{t-1} - Government Rice Credit Guarantee Scheme Fund in ‘000 ₦
TREND_t = Time Trend as a proxy of technology change
PYMR_t = Milling Rate of Paddy in %
REIM_t – Rice Import in Mt
NTRD_t – Total Rice Demand in Mt
REPC_t – Per Capita Domestic Demand of Rice in Kg Capita^{-1}
RERP_t – Retail Price of Rice in ₦ Mt^{-1}
WTRP_t – Retail Price of Wheat in ₦ Mt^{-1}
GNIPC_t – Gross National Income per Capita in ‘000 ₦
POP_t – Population in Millions
REWP_t – World Price of Rice in US$ Mt^{-1}
REIT = Rice import tariff in percent
EXRT_t – Nigerian Currency Exchange Rate in ₦ $\mathrm{US\$}^{-1}$

Model Estimation

In the estimation phase of this analysis, an autoregressive distributed lag (ARDL) approach was adopted due to some advantages it possesses such as its applicability to variables of mixed or single order of integration. The ARDL modelling approach has the following structure: -

$$y_t = \alpha + \beta x_t + \delta z_t + e_t \qquad (1)$$

the error correction version of the ARDL model is given by: -

$$\Delta y_t = \alpha_0 + \sum_{i-1}^{p} \beta_i \Delta y_t + \sum_{i-1}^{p} \delta_i \Delta x_i + \sum_{i-1}^{p} \varepsilon_i \Delta z_{t-1} + \lambda_1 y_{t-1} + \lambda_2 x_{t-1} + \lambda_3 z_{t-1} + \mu_t \qquad (2)$$

the first part of the equation with β, δ and ε represents the short-run dynamics of the model. The second part with λs represents the long-run relationship. The null hypothesis in the equation is $\lambda_1 + \lambda_2 + \lambda_3 = 0$, which means the non-existence of long-run relationship.

Model Validation

In time series forecasting, determining in advance the most effective method is usually impossible. The basic idea behind model reliability is to identify that which well explains the past behaviour of the time series variable under consideration. Two common approaches are commonly employed. In the first approach, a graphical method of constructing and then comparing line graphs of the actual data against values predicted by the model is performed. The second approach is statistical which involves a series of tests conducted on the model. In this study, both approaches were adopted including four statistical measures expressed as follows: -

Mean Absolute Error (*MAE*) $= \frac{1}{T}\sum_{t=1}^{T}\left|(Y_t^s - Y_t^a)\right|$ (3)

Mean Absolute Percent Error (*MAPE*) $= \frac{1}{T}\sum_{t=1}^{T}\left|\left(\frac{Y_t^s - Y_t^a}{Y_t^a}\right)\right|$ (4)

Root Mean Square Percent Error $= \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\frac{Y_t^s - Y_t^a}{Y_t^a}\right)^2}$ (5)

Theil's inequality coefficients (U) $= \frac{\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(Y_t^s - Y_t^a\right)^2}}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(Y_t^s\right)^2} + \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(Y_t^a\right)^2}}$ (6)

In each of these expressions, Y_t^s represents the forecasted value of Y in period t, Y_t^a represents the actual value of Y in period t and T is the number of periods in the simulated period. These quantities measure the differences between the actual values in the time series and the predicted or fitted values generated by the forecasting technique.

Projection Technique

In the second stage, the estimated model was used to project rice SSL for ten-years from 2018 base year. To obtain the projected values, the elasticities of the estimated model and annual rates of change of the associated variables were used. Thus:-

$lnY = \delta_0 + \delta_1 lnX_1 + \delta_2 lnX_2 + \delta_3 lnX_3 + \cdots + \delta_n lnX_n + \varepsilon$ (7)

Where, Y denotes an endogenous variable, X_i is independent variables with $i = 1, 2, 3 \ldots n$, δ_i with $i = 0,1,2,3 \ldots n$ are coefficients to be estimated and ε is error term.

The projections, represented by their rates of change are generated using the following equation:

$Y_t = Y_{t-1} + Y_{t-1}(\square Y)$ (8)

Where Y is the variable under consideration, ϕY is the annual growth rate for Y - either exogenously or endogenously determined, and t is the current year.

The annual rates of change for the endogenous variable were given by a generic formula of the form:-

$$\phi Y = \delta_1 * \square X_1 + \delta_2 * \square X_2 + \delta_3 * \square X_3 + \cdots + \delta_n * \square X_n \quad (9)$$

where ϕY is the calculated annual growth rate of the endogenous variable, Y, δ is the elasticity of variable Y with respect to X_i for $i = 1,2,3,\ldots n$, and ϕX_i is the annual percentage rate of change for variable X for $i = 1,2,3\ldots n$

Before commencing with the forecast exercise, a base year of 2018 was established. At this base year, the tariff rate is left at its initial 2018 rate of 70% while growth rates for the exogenous variables are referenced from their last five-year averages.

Results and Discussion

Unit Root and Cointegration Tests

In line with the objective of this study, it was necessary to test the data series for non-stationarity – a situation whereby data series exhibit time-varying mean or time-varying variance or both, thus, violating the classical econometric assumptions. Consequently, modelling non-stationary data using classical econometric techniques can lead to spurious regression results (Granger & Newbold, 1974), compromising its use in forecasting objectives. To test for stationarity, this study employed the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) Unit Root Tests. The findings (Table 2) showed that the regressors were all of I(1). Additionally, the result of the unit root test validated the adoption of the unrestricted ARDL Bound Test to estimate the model.

Table 2: ADF and PP Unit Root Tests (with intercepts)

Variable	ADF	PP	Conclusion

	Level t-statistic	First difference t-statistic	Level t-statistic	First difference t-statistic	
lnPYAH	-1.792	-8.090***	-1.998	-8.071***	I(1)
lnPYPP	-2.657	-6.801***	-2.616	-6.772***	I(1)
lnCVPP	-0.438	-8.814***	-0.697	-9.428***	I(1)
lnCGSF	-1.877	-4.033***	-1.593	-4.010***	I(1)
lnPYYD	-1.554	-8.142***	-1.669	-8.126***	I(1)
lnREPC	-1.080	-7.504***	-0.655	-7.709***	I(1)
lnRERP	-1.768	-6.559***	-1.767	-6.845***	I(1)
lnWTRP	0.170	-2.742***	-1.213	-8.859***	I(1)
lnGNIPC	0.453	-4.318***	0.113	-4.343***	I(1)

Following the stationarity test was a bounds test of cointegration to determine whether the variables share a long-run association. The bounds test is mainly based on the joint F-statistic in which its asymptotic distribution is non-standard under the null hypothesis of no cointegration. Therefore, the four specified equations were subjected to an F-test for the joint significance of the coefficients of the lagged levels of the variables. As a criterion, the null hypothesis of no cointegration is rejected when the value of the test statistic exceeds the upper critical bounds provided by Narayan (2005), otherwise it is accepted if the F-statistic is lower than the lower bounds value. Accordingly, based on the results in Table 3, the null hypotheses were rejected, thus indicating the existence of long run relationships (cointegration) between the variables of each of the four equations.

Table 3: ARDL bounds test of cointegration

Dependent variable	K	Lag	F-statistic	Narayan (2005) Critical values	
				I(0)	I(1)
lnPYAH	3	2	4.081*	2.933	4.020
lnPYYD	2	2	4.591*	3.373	4.377
lnREPC	3	2	11.023***	5.018	6.610
lnPYPP	1	2	6.497**	5.260	6.160

Note: ***, ** and * denotes significant at 1%, 5% and 10% levels, respectively

Estimated Long-run Coefficients

A presentation of the ARDL long-run coefficients of the estimated model including results of the necessary diagnostic statistics are provided in Table 3. In general, the estimated equations fitted the data in a manner consistent with economic theory. The statistical properties of the model viz Ramsey's RESET test for functional form misspecification, Breusch Godfrey LM (BG-LM) test for serial correlation, Breusch-Pagan-Godfrey (BP-G) test for heteroskedasticity and Jarque-Bera (JB) test for normality of residuals fell within acceptable statistical thresholds, and all the equations had at least 92% of their historical variations explained.

In the supply sub-model, the paddy area harvested was significantly influenced by the lagged area harvested and the government rice credit guarantee scheme fund. As reflected by the paddy's own price elasticity of 0.206, it was observed that the paddy area harvested was unresponsive to paddy producer price. It makes sense that the slow response could be caused by agricultural commodities' typically long production cycles, which make it challenging for producers to adjust production activities quickly. It follows that farmers' decisions about the size of their farms are only slightly influenced by paddy prices. Similar rice studies in Nigeria found slightly higher own-price elasticities of paddy. They reported 0.633 (Ayinde & Bessler, 2014), 0.23 (Takeshima, 2016) and 0.34 (Okpe, Abu, & Odoemenem, 2018), respectively. The rice credit guarantee scheme variable showed a positive relationship with paddy area harvested with a coefficient of 0.162 and had a statistically significant effect on paddy area harvested at a 5% level. As for paddy yield, the result showed that a 1% rise in the producer price of paddy will cause a yield improvement of 0.220%. This result paralleled Bansi's (2014) who observed a 0.210 elasticity. As expected, lagged yield had a positive effect on yield by about 0.49% because higher volumes of yield may drive producers to increase their investment in yield-enhancing inputs subsequent production seasons.

On the demand sub-model, all the featured variables carried their expected signs, more so, significantly. The own-price elasticity of rice was -0.321 and the cross-price elasticity was 0.193, meaning that a higher retail price of rice suppressed its quantity demanded. The relationship between per capita rice demand and income was described by the income elasticity of demand value of 0.95. This means that rice is a normal good, more so, a necessity, therefore, consumers' demands for rice are tied to their income levels - more incomes means more quantity demanded. The behaviour of wheat was expected since wheat is also a staple in Nigeria and therefore, a substitute. Other researchers like Makama (2017), found a higher own price elasticity (-0.55) for rice. In the paddy producer price equation, rice retail price was positive with an elasticity of 0.168.

Table 4: Estimated results of Nigeria's rice market model

Variable	Sub-model			
Regressor	Paddy harvested area	Paddy yield	Rice consumption per Capita demand	Producer price
Constant	9.520*** (3.830)	3.272 (2.724)	-8.799 (-4.350)	-0.622 (-0.807)
$PYAH_{t-1}$	0.260 (1.555)			
$PYPP_{t-1}$	0.206 (4.170)	0.220** (2.569)		0.985*** (38.915)
$CVPP_{t-1}$	-0.076 (-1.433)			
$CGSF_{t-1}$	0.162** (2.252)			
$PYYD_{t-1}$		0.488*** (3.557)		
$TREND_t$		0.292** (3.041)		
$REPC_{t-1}$			0.493*** (5.646)	
$RERP_{t-1}$			-0.321*** (-5.380)	
$WTRP_{t-1}$			0.193*** (3.754)	
$GNIPC_{t-1}$			0.951** (2.693)	
$REDP_t$				0.168 (1.588)
Diagnostic test				
Adjusted R^2	0.951	0.951	0.920	0.987
BG-LM	0.888[0.422]	0.932[0.437]	0.244[0.786]	2.675[0.084]
JB	19.556[0.000]	1.592[0.451]	1.037[0.595]	2.413[0.299]
RESET	0.084[0.774]	0.008[0.929]	2.633[0.116]	3.447[0.072]
BP-G	1.051[0.406]	0.695[0.601]	0.884[0.542]	1.431[0.253]

Note: ***, ** and * denote significant at 1%, 5% and 10% levels, respectively. Figures in parenthesis (…) are t-statistics while figures in brackets […] are p-values.

Model Validation

As a necessary step in time series forecasting studies, the estimated model's forecasting ability was examined to establish its validity and reliability. This was done via both graphical and statistical methods. A visual examination of the graphical method depicted in Figure 1 shows that each of the endogenous variables tracked fairly well over its historical data. Although some variations were observed, this is not uncommon (Pindyck & Rubinfeld, 1998).

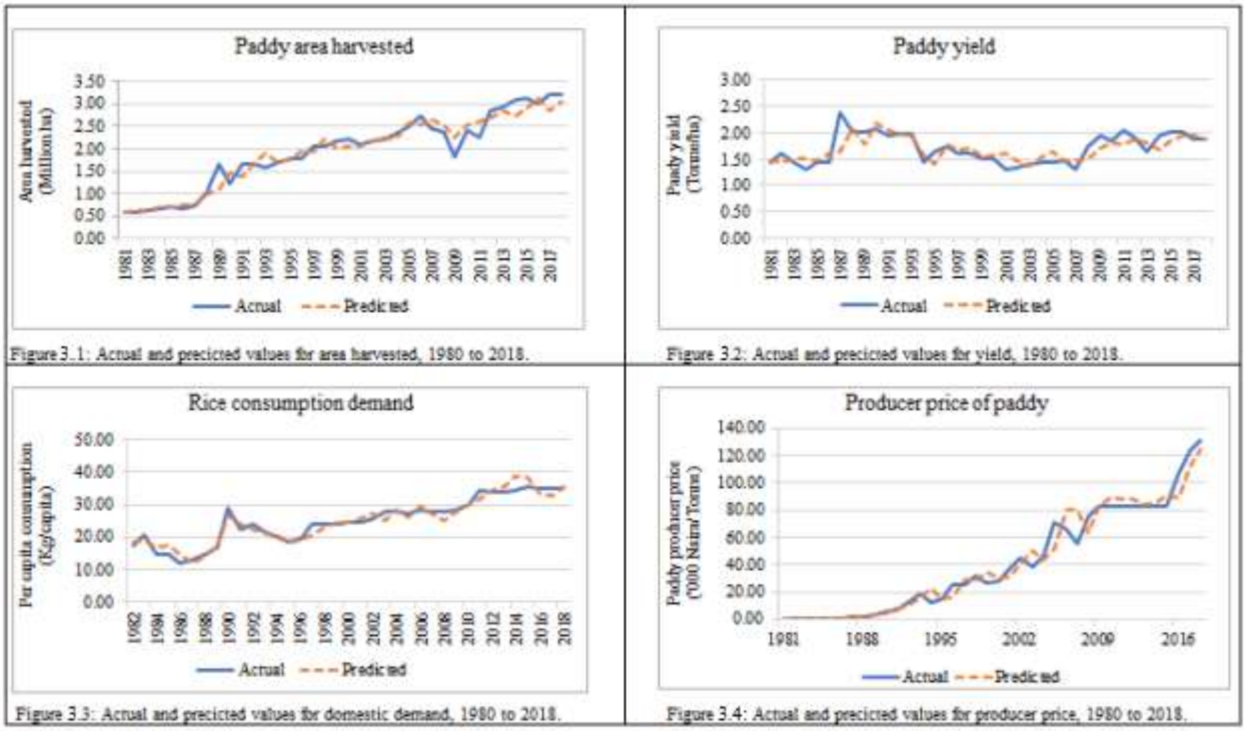

Figure 3.1: Actual and precicted values for area harvested, 1980 to 2018.

Figure 3.2: Actual and precicted values for yield, 1980 to 2018.

Figure 3.3: Actual and precicted values for domestic demand, 1980 to 2018.

Figure 3.4: Actual and precicted values for producer price, 1980 to 2018.

Figure 3: Graphical representation of within-sample validation

Results of the validity tests are presented in Table 4 and they allow a satisfactory confirmation of the model's forecasting ability and performance. The value of the MAPE revealed a reasonable forecast accuracy since the simulated values were off by less than 3%. The RMSPE of the yield equation was quite high but this can be explained. According to literature, the RMSPE can be misleading when the variable under consideration has a wide variability or volatility (as is the case with the historical yield data) which can lead to larger errors when calculating the percentage errors. It can also be due to unpredictability nature of these types of data such as yield. Additionally, if the yield equation has small magnitudes, any minute error of prediction creates a high proportion of error when such error is compared to the small actual value. In such cases, other model validation measure such as Theil statistics would be more convincing. The individual components of U^T showed that the model had a good fit with little to no systematic forecasting error and overall, possessed a good forecasting ability. This was supported by Pindcyk and Rubinfield (1998) who suggested that U^b values above 0.1 or 0.2 would indicate the presence of systemic bias, necessitating a possible re-specification of the model.

Table 5: Results of Within-Sample Validation

Statistic	Notation	Endogenous variable			
		PYAH	PYYD	REPC	PYPP
Mean Absolute Error	MAE	0.077	0.093	0.065	0.216
Mean Absolute Percent Error	MAPE	0.533	1.271	2.113	2.541
Root Mean Squared Percent Error	RMSPE	0.763	24.53	2.501	3.030
Theil Inequality Coefficient	U^T	0.004	0.008	0.014	0.014
Bias proportion	U^B	0.000	0.001	0.000	0.032
Variance proportion	U^V	0.014	0.015	0.055	0.193
Covariance proportion	U^C	0.986	0.984	0.945	0.775

Rice Self-sufficiency Level Baseline Projections

The basic idea in this analysis was to replicate and project the market situation using historical data from 1980 to 2018. At a SSL of 67% in 2018, Nigeria was far behind its official goal of reaching SSL by the year 2020, as targeted in the Agricultural Promotion policy of reaching rice self-sufficiency by 2020. In an effort to use the latest available estimate, 2018 was set as the baseline in which official import tariff was 70% while a last five year average growth rates were used for the exogenous variables. A ten years projection reported in Table 6 shows a generally uneven trend. It revealed a sharp drop from the baseline estimate of 67% to 51.34% in 2019. Nonetheless, it gradually increased in 2022 to reach 70.96% in 2028, while maintaining a yearly average of 53%. This behaviour was unsurprising for two reasons. First, the projected trend seemed to mimic the erratic nature of the historical data (Figure 1). Second, it reflected the unstable nature of Nigeria's rice production-consumption dynamic, especially considering the smallholder nature of the country's production systems. Overall, these results indicated the country's inability to meet its own population's demand for rice. Other related variables are explored to understand their performances as they influence SSL.

Rice production will average 4.30 Mt per year, mainly as a result of an average yield of 2.12 Mt ha^{-1}, equivalent to a 3.06% growth rate. Yield growth (3.06%) appeared to be the primary driver for paddy production relative to the paddy area harvested. Complementing the yield growth is an annual area harvested growth of 1.14% so that projections topped 3.46 hectares in 2028. Together, these variables spiked a 4.25% growth in rice production, which is expected to reach 5.44 million Mt in 2028.

Average annual figures showed demand increasing by 0.65% per year, averaging 8.15 Million Mt. The highest estimates were recorded in 2022 with 8.63 million Mt of rice to be demanded compared to a rice production volume of 3.91 million Mt in the same year. This meant that, despite the growth in rice production by 2028 (5.44 million Mt), it would be insufficient to satisfy a demand of 7.66 million Mt by 2028. As explained earlier, demand for rice is driven by population which has a 2.4% annual growth rate in 2022 (World bank database) and urbanisation which has a growth rate of 4.1% in 2020 (IndexMundi database). Therefore, imports will be unavoidable with its forecast averaging 3.85 million Mt yearly. At the initial stage, demand increases due to quality differentials in favour of imported rice which urban households usually prefer. However, consistent with the theory of demand, there is a drop in demand from 2023 due to high retail price which may cause affordability concerns resulting in a substitution reaction for wheat in the long run.

As an important factor in total demand, per capita demand started at 36.41 kg Capita^{-1} in 2019, it increased to 40.64 kg Capita^{-1} in 2021 but then declined to 30.87 kg Capita^{-1} in 2028. Two factors could explain this behaviour. First, retail prices gained, owing to increasing exchange rates and higher world market prices. Consequently, consumers will experience higher retail prices of ₦409 thousand Mt^{-1} on average, equivalent to an 11.11% yearly growth rate, causing a reduction in per Capita demand. Secondly, this weakening rice consumption could result from the positive income elasticity. Based on the estimation result, rice was determined to be a normal good. As income increased, consumers respond initially by increasing rice consumption, but in the long run, a continuous rise in income could encourage consumers taste to evolve in favour of other healthier eating habits featuring options like brown rice and basmati rice. Other additional element of uncertainty, such as high exchange rate and high inflation can cause a shift from imported rice for domestically produced rice in the long run. Overall, the projections show that the demand for rice is expected to be shaped by the population growth, price of rice and income. Their individual influences on quantity demanded are considered while keeping other factors constant in line with economic theory. Nonetheless, their aggregate influence results in a declining per capita consumption in the long run projection figures which began in 2023.

The results of this study revealed a bleak outlook for Nigeria's rice self-sufficiency goal. This gloomy future was shared by Van Oort et al. (2015) adopted a yield gap assessment technique to determine Nigeria’s SSL of 54% for 2025 projection, given a one one Mt ha^{-1} yield increment.

An average SSL of 53% for the 10-year projected period means that Nigeria will need to almost double its average production volumes of 4.3 million Mt or increase production by about 47% to be self-sufficient in rice. Decomposing the rice production sub-model from a yield perspective to consider this goal, IRRI estimates the required yield to attain rice self-sufficiency for Nigeria is 5.30 Mt h^{-1} (Gloria-Pelicano & Prandelli, 2013). This means that Nigeria will have to more than double its current average yield of two metric tonnes per hectare. On a positive note, this seems feasible, given the tremendous rice production potential of the country available for intensive exploitation for a productive and sustainable national rice market.

Table 6: Summary of Nigeria's rice market projection

Variable	Unit	Projection												
		2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	Average 2019 - 2028	
Supply													μ	Δ
Harvested area	Million ha	3.20	3.13	3.12	3.12	3.12	3.13	3.17	3.22	3.28	3.36	3.46	3.21	1.14
Paddy yield	Mt h^{-1}	1.88	1.90	1.94	1.96	1.99	2.03	2.09	2.16	2.25	2.36	2.49	2.12	3.06
Paddy production	Million Mt	6.12	5.95	6.05	6.11	6.21	6.37	6.61	6.94	7.38	7.93	8.63	6.82	4.25
Rice production	Million Mt	5.34	3.75	3.81	3.85	3.91	4.01	4.17	4.37	4.65	5.00	5.44	4.30	4.25
Rice import	Million Mt	3.00	3.55	4.36	4.70	4.72	4.55	4.26	3.87	3.41	2.86	2.23	3.85	-4.27
Demand														
Domestic demand	Million Mt	6.90	7.30	8.17	8.55	8.63	8.56	8.42	8.24	8.05	7.86	7.66	8.15	0.64
Per capita demand	Kg Capita^{-1}	35.23	36.41	39.79	40.64	40.08	38.83	37.29	35.65	34.01	32.41	30.87	36.60	-1.72
Price														
Retail Price	'000 ₦ Mt	305.04	243.33	270.36	300.39	333.76	370.84	412.03	457.80	508.65	565.16	627.93	409.02	11.11
Producer price	'000 ₦ Mt^{-1}	52.94	53.92	53.06	53.22	54.37	56.54	59.83	64.36	70.37	78.15	88.13	63.19	5.71
Self-sufficiency														
SSL	Per cent	64.00	51.34	46.64	45.06	45.33	46.88	49.46	53.05	57.71	63.60	70.96	53.00	3.87

Note: Mt denotes metric tonnes, μ denotes variable average and Δ denotes average growth rate in percentage.
Note: 306.08 Naira = 1 US dollar
Note: 2018 is baseline

Conclusion

Strengthening rice self-sufficiency has gained priority in Nigeria's staple food policy agenda. Nonetheless, there is a lingering situation of demand-supply imbalance. An important step is to understand the dynamics of the demand for food staples and production potentials in relation to rice SSL. Such analysis serves as a valuable tool for guiding policy design that could help to create efficient agricultural food market systems and promote sustainable economic development. This study empirically projected rice SSL, which will help provide insight into the ability of the country to achieve rice self-sufficiency in the future and thus guide the formulation of future national rice market policies. The analysis adopted a theory-oriented market model for a non-storable commodity to provide a 10-year projection of rice self-sufficiency level for Nigeria based on an econometric approach. The model performance was validated by the results of the statistical tests showing appreciable model forecasting strength. The result of this paper underscored a broader policy message that, given the current policy environment of the country's rice market, achieving self-sufficiency is unfeasible in the future, despite many past intervention projects. Such a situation will push the country towards a continuous dependence on imports at the expense of affordable domestically produced substitutes, consequently creating a risk of a deteriorating rice market as well as threatening food security. One effective way to improve SSL is to design policies towards investing in yield enhancing technology. In this study, the appreciation for adopting the econometric market model approach extends beyond producing the projections of FSS level to highlighting the dynamics of the key variables as they influence the country's rice market system.

Since this article attempted to replicate the Nigerian rice market as a foundation upon which a projection was made, some limitations are worth mentioning. First, the initial attempt for model specification included some weather related variables like rainfall and temperature and policy variable like fertilizer subsidy which were theorised to affect paddy production in the national paddy production sub-model. However, the estimated functions had unacceptable results in terms of their signs and their result diagnostic tests, hence the model had to be re-specified with those variables removed for an acceptable result. Secondly, there were issues of few missing data entries for some variables and these issues were resolved by interpolation. Ultimately, the presented results were based on available data and are believed to be the acceptable of the specifications attempted from an economic theory point of view.

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