



## Forecasting of Rice Self-Sufficiency in the Benin Republic Using ARIMA Model

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### ABSTRACT

Rice is one of the staple foods in the Benin Republic. Annual rice consumption is increasing faster than annual rice production. That is why Benin is not yet self-sufficient in rice production. To meet the local demand, huge quantities of rice are imported. For country planning, forecasting is the main tool for predicting rice variables. This paper describes an empirical study that used a time series modeling approach (Box-Jenkins' ARIMA model) to forecast rice production, rice consumption, rice importation, rice exportation and finally rice self-sufficiency in Benin. Based on ARIMA model, the rice self-sufficiency rate in Benin is forecasted to be 47%, 56%, 58%, 59% and 68% respectively in 2019, 2020, 2021, 2022 and 2023. The forecasts would be helpful for the policy makers to foresee ahead of time the future requirements of rice production, adopt appropriate measures to develop rice sector for effective rice self-sufficiency and to reduce rice importation.

#### Keywords:

ARIMA model  
Importation  
Riceproduction  
Riceconsumption  
Self-sufficiency  
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### 1. Introduction

In most African countries, the agricultural sector occupies an essential place in the national economy. In Africa, every 1% increase in agricultural productivity reduces poverty by 0.6%, and a 1% increase in production reduces the number of people living with less than one dollar a day by 6 million (Thirtle et al. 2003). Two out of five people in Africa still live in extreme poverty (Beegle et al. 2016) and increasing agricultural productivity is crucial for reducing poverty (Christiaensen et al. 2011). Agriculture is the primary production activity of rural livelihoods in sub-Saharan Africa, and on average 92% of rural households is engaged in farming (Davis et al. 2017). Rural

Households also derive about two-thirds of their income from on-farm agriculture, compared with one-third (on average) in other developing countries (Christiaensen, 2017).

As a result, the economic "take-off" of Sub-Saharan African countries in general and of Benin, in particular, is closely linked to agriculture (Aho and Kossou, 1997). The agricultural sector contributes 38% to Gross Domestic Product (GDP) in Benin (PNUD-IDH, 2011). Crop production is the primary production activity in the agricultural sector and on average contributes 23% to GDP (FAO, 2012a).

In the crop production sub-sector, cereal products hold the prominent place, and among cereals, corn, sorghum, and rice are the most important ones. Local rice production provides 1% contribution to GDP (MAEP, 2007). In order to satisfy domestic consumption and re-exportation, Benin imports huge quantities of rice. West Africa is experiencing rapid growth in rice consumption due to population growth, urbanization and increasing purchasing power (Fofana et al. 2014). At the same time, rice is the most critical nutritional source and a highly strategic food commodity for the West African region (Seck et al. 2013). Rice is the staple food of more than 750 million people in sub-Saharan Africa (USDA, 2016). Average annual

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rice consumption in sub-Saharan Africa (4%) is increasing faster than rice production (3.3%) (LARES, 2008). Longtime considered as a luxury food consumed during feast days; rice became part of eating habits of the populations of Benin. In Benin, while rice consumption is increasing, only 7% of the rice production potential (land and water resources) is used (JACQUES, 2008). In the country, rice ranks third regarding cereal production after maize and sorghum (ABEL, 2009) and is the second most crucial cereal regarding consumption after maize. Despite the progress realized in local rice production in sub-Saharan Africa after the food crisis of 2007-2008, rice demand has never been met; rice importation dependence is still around 50% and local rice production represents only 60% of domestic consumption (Saito et al. 2015, USDA, 2016). The rapid increase in domestic rice production is a significant challenge for Sub-Saharan Africa (Secket al. 2012).

Given these situations and given that Benin has enormous potential for rice cultivation of which less than 8% is currently exploited, it is imperative to think of increasing the local supply of rice in order to satisfy local demand, reducing rice importation and increasing rice exportation.

This study aims to forecast rice production, rice consumption, rice importation, rice exportation and finally rice self-sufficiency over the next five years in Benin.

## 2. Material and method

### 2.1. Methods of data collection

The data used in this study were obtained from the official websites of the Ministry of Agriculture of Benin (MAEP) and Food and Agricultural Organization (FAO). For the time series data, we considered different periods: area, paddy rice and rice importation cover the period 1961-2016; rice exportation covers the period 1961-2015; milled rice and rice consumption cover the period 1961-2013. We took different periods for the time series because rice data of Benin are not available in the same period.

In this study, the self-sufficiency level is calculated by using the following formula. Self-sufficiency level = (Usable production/Domestic use) x 100 (FAO, 2012b; Van Oort et al. 2015; Demirbaş et al. 2017).

### 2.2. Methods used in data analysis

Different models are used in data estimation. In agriculture domain, ARIMA model was used in many studies to forecast milled rice production (Suleman and Sarpong, 2012), to forecast rice area, production and productivity (Rahman et al. 2016; Hemavathi and Prabakaran, 2018), to forecast the price of medium quality rice to anticipate price

fluctuations (Ohyver and Pudjihastuti, 2018), to forecast maize production (Sharma et al., 2018). In this study, ARIMA model is also used for data estimation.

### ARIMA model

Future estimation of a variable can be made only by using the variable itself without any other variables. These estimates are not based on a theoretical model. The movement of the variable in the past can be used to predict future movement. A linear time series models introduced by Box and

Jenkins (1970), are now widely used and accepted. According to them, the ARIMA model is

denoted by ARIMA (p, d, q) where 'p' is the order of the autoregressive process (AR); 'd' is the order of homogeneity i.e. the number of difference to make the series stationary; and 'q' the order of the moving average process (MA) (Box and Jenkins, 1970; Awajan et al., 2017).

The general form of the ARIMA (p, d, q) is

$$Y_t = \zeta + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \dots + \beta_p Y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q} \quad (\text{Kennedy, 2006:351}).$$

Here,  $Y_t$  gives the time series,  $\varepsilon_t$  error term,  $\beta$  model estimator,  $\zeta$  time series average.

Before doing an analysis of time series, we plot the data by using standard plots and summary statistics to see the behavior of the data. The sample ACF and the PACF pattern were done to see whether given data is stationary in its level and variability. Apart from rice exportation and rice consumption variables, the other variables are non-stationary in level since they have not fluctuated around constant mean and variance. Then we took the first difference of the data values and we selected the stationary levels of the data (Table 1). The selection criterion is the probability (5%). To determine the orders (p, q) we referred to ACF and the PACF pattern. We estimated the parameters and fixed the fitted ARIMA model. Therefore, the fitted ARIMA model is the one that has more significant coefficients, less volatile, a higher R-squared, a lower Akaike Criterion (AIC) and a Theil's inequality coefficient less than 1 (Table 2). The final step of the validity of the fitted model was based on the distribution of residuals and of residuals square to find out whether the residuals are a white noise or not and find out whether all the information contained in the series have been exploited or not.

### Test of forecast accuracy of the Box Jenkins method.

Theil's U statistic measures the forecast accuracy (Theil, 1958). In this study, Theil's inequality coefficient is used to measure the predictive accuracy of models.

Theil Inequality Coefficient

$$U = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (\Delta \hat{Y}_i - Y_i)^2}}{\sqrt{\frac{1}{n} \sum_{i=0}^n (\Delta Y_i)^2}}$$

$\Delta Y_i$  = actual change of variable

$\Delta \hat{Y}_i$  = predicted change of variable

n = Number of observations

The coefficient U is bounded between 0 and 1 ( $0 \leq U \leq 1$ ). Theil's inequality coefficient shows the predictive accuracy of the model. This coefficient should be less than 1 (Vergil and Ozkan, 2007; Okur, 2009, Özer and İlkdoğan, 2013). The prediction of the model will not be accurate if the calculated value is greater than 1. In that case, the model is not the most appropriate one. In This

Table1

The results of ADF unit root test.

Variables	Test atlevel					First difference test				
	Lag	Model	ADF	Critic	Processus	Lag	Model	ADF	Critic	Processus
Cons_b	8	Trend et constante	-5.26	-5.34	I (0)					
Exp01	8	Trend et constante	-5.26	-5.34	I (0)					
Imp	7	Trend et constante	4.43	-4.85	Non stationnaire	0	constante	11.52	-4.85	I (1)
PROB_b	7	Constante	0.73	-4.44	Non stationnaire	0	Trend et constante	-7.25	-4.85	I (1)
Prod_p	5	Trend et constante	2.62	-4.65	Non stationnaire	0	constante	-6.43	-4.44	I (1)
Sup	2	Trend et constante	4.38	-4.85	Non stationnaire	7	Trend et constante	-5.94	-4.85	I (1)

Tests are significant at 5%.

Table2

Summary of models

Variables	Order of integration	Model	Adjusted model	Theil's inequality coefficient	Probability
Cons_b	I (0)	AR (1)	AR (1) AR (2) MA (7)	0.28	0.001
Exp01	I (0)	ARMA (1,1)		0.79	0.000018
Imp	I (1)	ARIMA (1,1,1)		0.52	0.00061
Prod_b	I (1)	ARIMA (3,1,3)		0.43	0.007
Prod_p	I (1)	ARIMA (5, 1, 3)		0.29	0.00015
Sup	I (1)	ARIMA(1,1, 12)		0.31	0.00016

The Theil's inequality coefficients for all the models are less than 1. So, the selected models are good for the prediction.

study, Theil's inequality coefficient is used to select the most appropriate model for the estimation (Table2).

### 3. Results and Discussion

#### 3.1. Unit root test

Augmented Dickey-Fuller test was carried out for the stability test. After the stationary studies of the series, only consumption and exportation series are stationary in level. Import, white rice production, paddy production and area series are stationary in first difference (Table 1).

## 3.2. Estimates of rice consumption

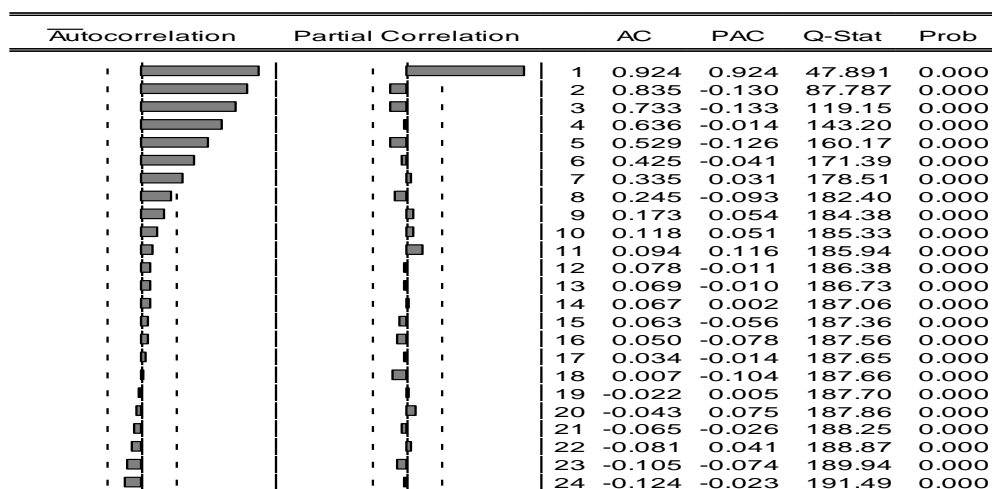


Figure1

Rice consumption ACF and PACF for stationary series.

The rice consumption series is an I(0). By observing the Figure1, the model to be estimated is AR (1) and its values are shown in the table3.

Table3  
The values of AR(1) model

Model	Coefficient	Std. Error	t-Statistic	Probability
AR(1)	0.995	0.027	36.609	0.000

The residuals correlogram shows that there is unused information in the model like MA (3) and

Table4  
The values of R(2), AR(1) and MA(3) models

	AR (2)	AR (1) and MA (3)
Significant coefficients	2	2
Sigma <sup>2</sup> (volatility)	5.52*10 <sup>8</sup>	5.47*10 <sup>8</sup>
R <sup>2</sup> adjusted	0.98	0.98
AIC	23.21	23.22

The most appropriate model is the one that has more significant coefficients, less volatile, a higher R-squared, and a lower Akaike Criterion (AIC). This model is the model AR (2). To validate this model, we analyzed the correlogram of residuals and residuals squared.

When one still observes the correlogram of the residuals squared, one notices that there is serial

AR (2). That's why we need to estimate the adjusted model and choose the most appropriate model.

autocorrelation. It must be corrected by integrating an AR (7) or MA (7). After estimation, it is the MA (7) that corrects it (Table4).

The correlogram of the residuals on this adjusted model shows that all the information is integrated into the model and the correlogram of the residuals squared shows that there is no more serial correlation.

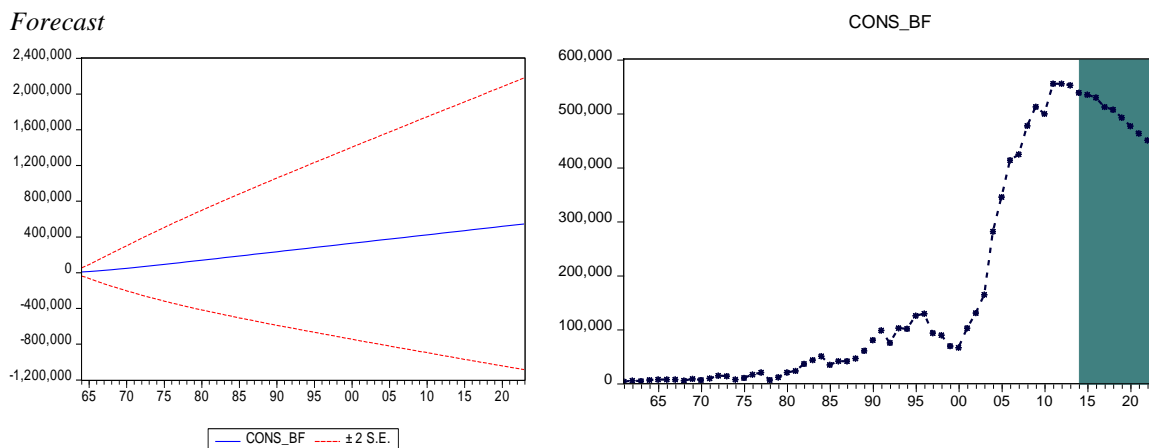


Figure2  
Plot of rice consumption forecast.

Table4  
Forecast values of rice consumption results

Year	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Forecast (ton)	538003.5	534626.6	529279.5	511713.1	506690.0	491890.5	476481.4	462716.0	450114.1	438388.4

Rice consumption will decrease from 491890.5 tons in 2019 to 438388.4 tons in 2023 (Table5, Figure2).

3.3. Estimates of rice exportation

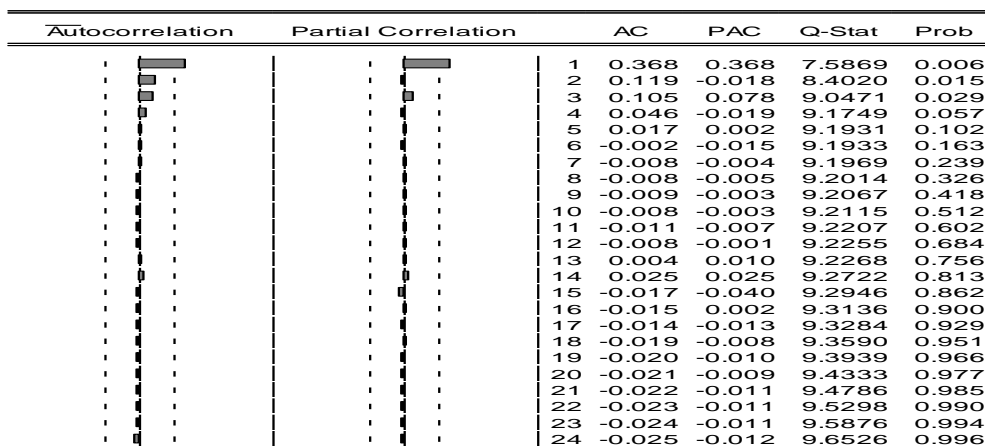


Figure3  
Rice exportation ACF and PACF for stationary series.

The Rice exportation series is an I(0). By observing the Figure3, the model to be estimated is the ARMA model (1,1) and the its values are shown in the table5

Table5  
The values of AR(1) and MA(1) models

Model	Coefficient	Std. Error	t-Statistic	Probability
AR(1)	0.292	0.801	0.365	0.016
MA(1)	0.081	0.907	0.089	0.029

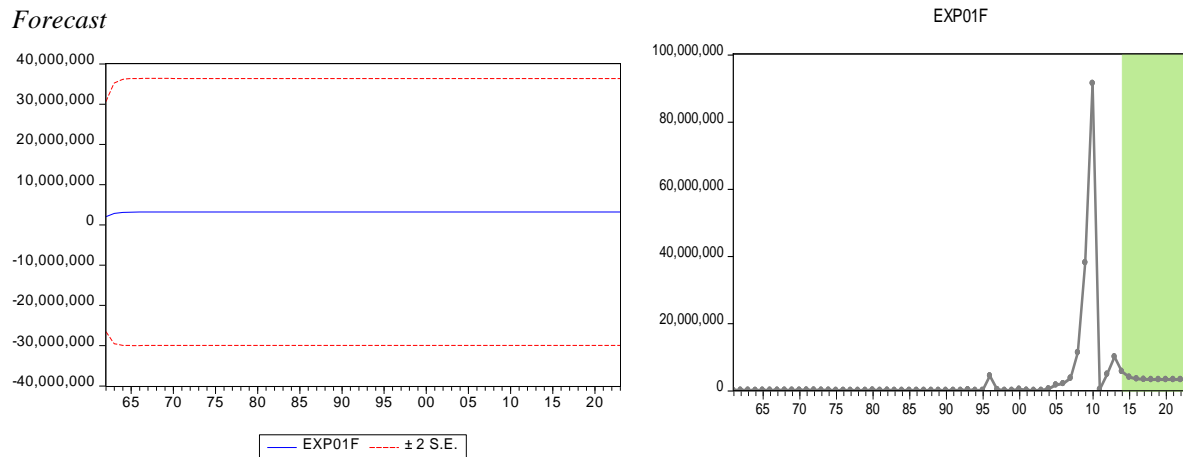


Figure4  
Exportation forecast graphs

Table6  
Forecast for rice exportation

Year	2016	2017	2018	2019	2020	2021	2022	2023
Forecast (ton)	3426473.63	3278216.33	3234802.85	3222090.29	3218367.73	3217277.67	3216958.47	3216865

Rice Exportations will decrease slightly from 3222090.29 tons in 2019 to 3216865 tons in 2023(Table6, Figure4).

3.4. Estimates of rice importation

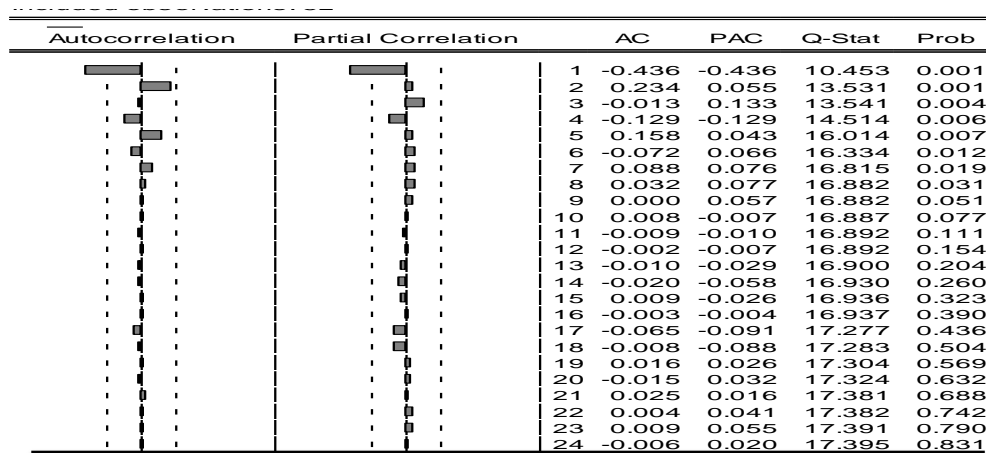


Figure5  
Rice importation ACF and PACF for stationary series.

The series of import is an I(1). By observing the and the its values are shown in the table7. Figure5, the model to be estimate is ARIMA(1,1,1)

Table7  
The values of AR(1) and MA(1) models

Model	Coefficient	Std. Error	t-Statistic	Probability
AR(1)	-0.749	0.225	-3.315	0.0018
MA(1)	0.251	0.494	0.507	0.0061

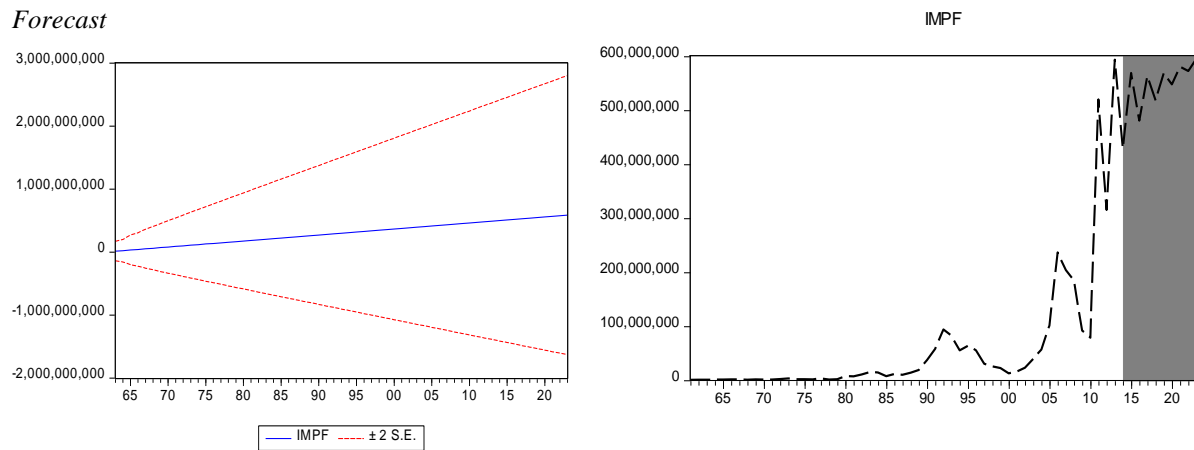


Figure6  
Plots of importation forecast

Table8  
Forecast for rice importation

Year	2017	2018	2019	2020	2021	2022	2023
Forecast( ton)	563000000	518000000	569000000	547000000	580000000	572000000	595000000

Imported rice will decrease from 569000000 tons in 2019 to 595000000 tons in 2023 (Table8, Figure6). These quantities of imported rice meet both domestic demand and re-exportations to neighboring countries.

3.5. Estimates of milled rice

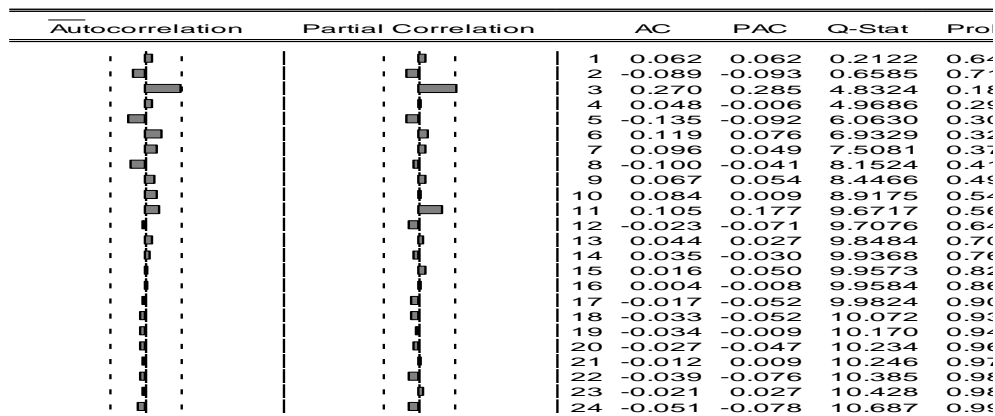


Figure7  
Milled rice ACF and PACF for stationary series

The series of consumption is an I(1). By observing the Figure7 the model to be estimated is

ARIMA(3,1,3) and the models values are shown in the table9.

Table9  
The values of AR(3) and MA(3) models

Model	Coefficient	Std. Error	t-Statistic	Probability
AR(3)	0.811	0.316	2.564	0.013
MA(3)	0.066	0.501	0.132	0.0084

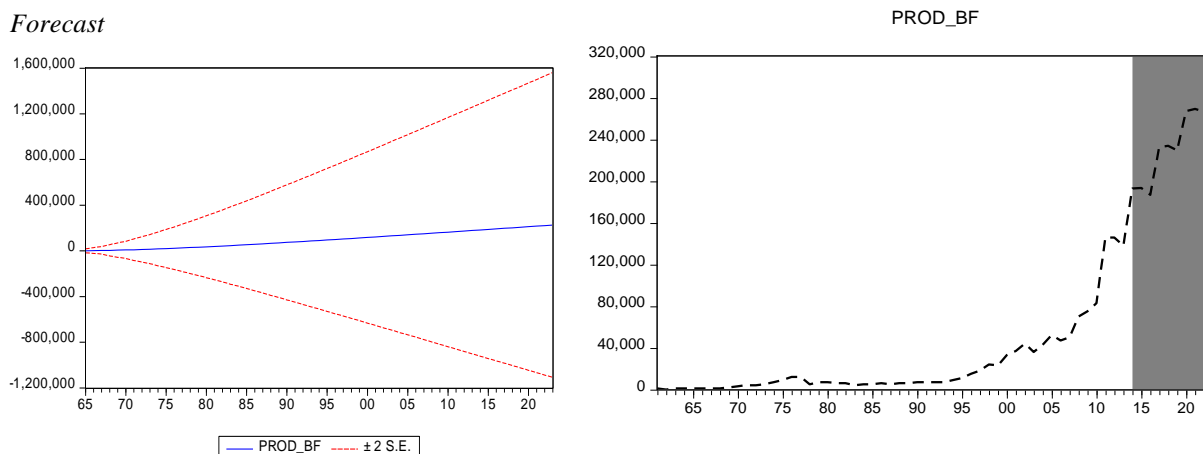


Figure8  
Plot of milled rice forecast

Table10  
Forecast for milled rice

Year	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Forecast (ton)	193056.2	193612	186993.7	232599.9	233974.2	229526.1	267462.9	269501.5	266814.8	298527.1

Milled rice will increase from 229526.1 tons in 2019 to 298527.1 tons in 2023 (Table10, Figure8).

3.6. Estimates of paddy rice production

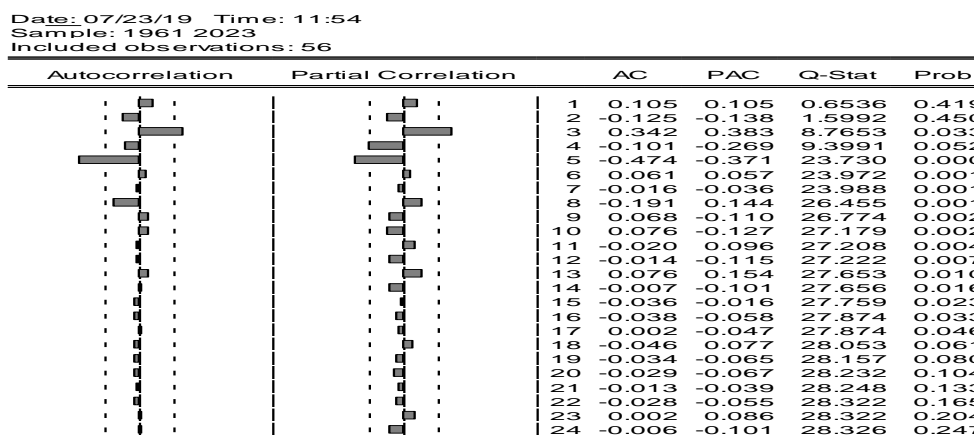


Figure9  
Paddy rice ACF and PACF for stationary series.

The series of paddy rice is an I(1). The analysis of the ACF and PACF functions allows us to retain

the following competing models (3,1,5); ARIMA (5, 1, 3); ARIMA (3,1,3); ARIMA (5,1,5)

Table11  
Comparison of different ARIMA models with model fit statistics for paddy rice

	ARIMA (3,1,5)	ARIMA (5, 1, 3)	ARIMA (3,1,3)	ARIMA (5,1,5)
Significant coefficients	2	2	0	0
Sigma <sup>2</sup> (volatility)	1.74.10 <sup>8</sup>	1.65.10 <sup>8</sup>	2.58.10 <sup>8</sup>	2.03.10 <sup>8</sup>
Adjusted R <sup>2</sup>	0.4504	0.4791	0.1840	0.35
AIC	22.01	21.97	22.37	22.16

The most appropriate model is one that has more significant coefficients, less volatility, a higher R-squared, and a lower Akaike Criterion (AIC).

Based on the Table11, the model ARIMA (5,1,3) was selected as the most appropriate one.



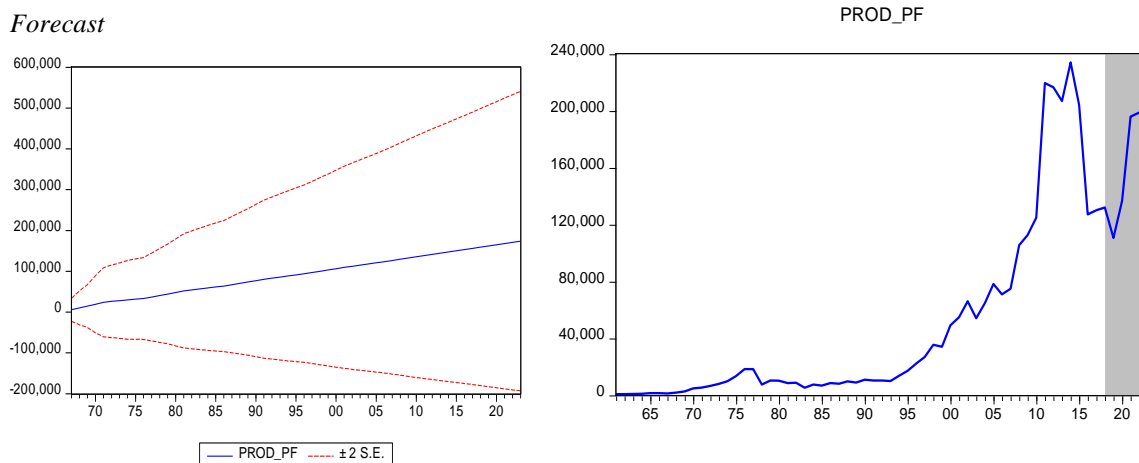


Figure10  
Plots of paddy forecast

Table12  
Forecast for paddy rice

Year	2017	2018	2019	2020	2021	2022	2023
Forecast (ton)	130189.8	132034.3	110682.8	136757.4	195994.9	198872.7	202584.1

Paddy rice will increase from 110682.8 tons in 2019 to and to 202584.1 tons in 2023 (Table12, Figure10).

3.7. Estimates of area of rice production

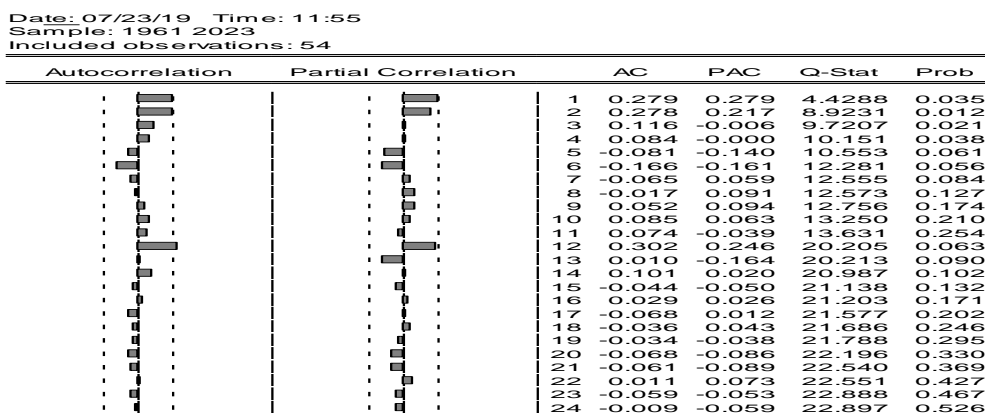


Figure11  
Area ACF and PACF for stationary series

The series of area is an I(1). The analysis of the ACF and PACF functions allows us to retain the following competing models: ARIMA (1,1,12);

ARIMA (12, 1, 1); ARIMA (12,1,12); ARIMA (1,1,1).

Table13  
The values of ARIMA (1,1,12); ARIMA (12, 1, 1); ARIMA (12,1,12) ; ARIMA (1,1,1)

	ARIMA (1,1,12)	ARIMA (12, 1, 1)	ARIMA (12,1,12)	ARIMA (1,1,1)
Significant coefficients	1	2	1	1
Sigma2 (volatility)	4583815	6257622	4707474	8620418
Adjusted R2	0.5030	0.3215	0.48	0.06
AIC	18.70	18.75	18.77	18.95

The most appropriate model is one that has more significant coefficients, less volatility, a higher R-squared, and a lower Akaike Criterion (AIC). Based

on the Table13, the ARIMA model (1, 1, 12) was selected as the most appropriate one.

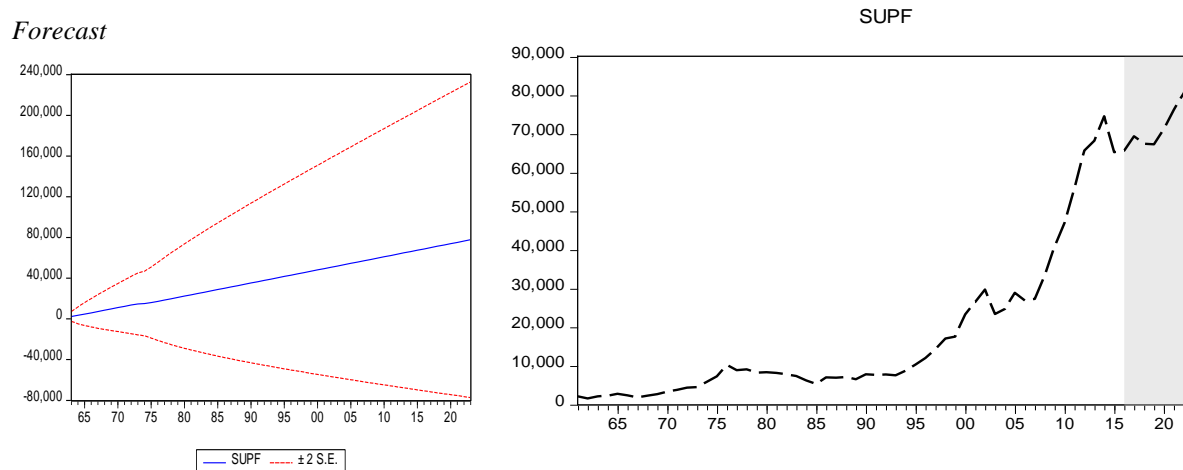


Figure12  
Area forecast graphs

Table14  
Forecast for area

Year	2017	2018	2019	2020	2021	2022	2023
Forecast (ha)	69394.72	67459.67	67317.95	71249.31	76254.26	80540.58	87708.02

The cultivated area will increase from 67317.95 ha in 2019 to 87708.02 ha in 2023 (Table14, Figure12).

Table15  
Self-sufficiency rate (2019-2023)

Year	2019	2020	2021	2022	2023
Milled rice (ton)	229526.1	267462.9	269501.5	266814.8	298527.1
Rice consumption (ton)	491890.5	476481.4	462716	450114.1	438388.4
Self-sufficiency (%)	47	56	58	59	68

Based on Table15, one observes that the rate of self-sufficiency will increase and will reach its peak (68%) in 2023. It can be concluded that Benin will continue importing large quantities of rice to meet domestic demand and fill the gap of about 32% of the self-sufficiency rate remaining during the next five years.

According to estimates of the Ministry of Agriculture of Benin, Benin was expected to reach its self-sufficiency level in rice production since 2013 through domestic production (MAEP, 2010). However, this goal could not be achieved due to inadequate agricultural policies. Right now, the self-sufficiency level in rice production is around 60% and this, because of insufficient domestic production.

#### 4. Conclusion and Suggestions

This study aims to give an overall idea of the rice sector in Benin and to forecast the variables of rice over the next five years by using the model. As a result, the self-sufficiency level will not be reached during the next five years. It will be about 68%. The fact is that annual rice consumption is increasing faster than annual rice production in Benin and in sub-Saharan Africa. Between 2010

and 2035, rice demand in sub-Saharan Africa is expected to increase by 130% (Secket al. 2012). Rice importations are likely to lose foreign exchange reserves and increase poverty and food insecurity. The rapid increase in local rice production is a significant challenge for sub-Saharan Africa (Catherine and Chapoto, 2017). To meet local consumption growth, rice production policies need to be redirected and revised. Because importation dependence can seriously affect food security and political stability, as demonstrated during the 2007-2008 food crisis (Berazneva and Lee, 2013). Sustainable food security cannot be based on importations, and it should be found on the development of domestic production for adequate protection against fluctuations in world prices (Larochea and Postolle, 2013).

#### 5. References

- Abel G J (2009). Etude sur le développement des filières riz et maraichage au Bénin. CTB ; pp.77.
- Aho N, Kossou D (1997). Précis d'Agriculture Tropicale : Bases et Eléments d'Application. Edition du Flamboyant :Cotonou.
- Awajan AM, Ismail MT, Al Wadi S (2017). A hybrid EMD-MA for forecasting stock market index. Italian Journal of Pure & Applied Mathematics, 38(1), 1-20.

- Beegle K, Christiaensen L, Dabalen A, Gaddis I (2016). Poverty in a Rising Africa. Washington, DC: World Bank. © World Bank. <https://openknowledge.worldbank.org/handle/10986/22575> License: CC BY 3.0 IGO.
- Berazneva, Lee (2013). Explaining the African food riots of 2007–2008: An empirical analysis. *Food Policy*, 39, 28–39.
- Box GEP, Jenkins GM (1970). *Time series analysis: Forecasting and control*, San Francisco: Holden-Day.
- Catherine C (2017). Limits to Green Revolution in rice in Africa: The case of Ghana. pp: 1-18.
- Christiaensen L (2017). A synthesis. February 2017, *Food Policy* 67, 1–11.
- Christiaensen L, Demery L, Kuhl J (2011). The (evolving) role of agriculture in poverty reduction--An empirical perspective. *Journal of Development Economics*, Elsevier, vol. 96–2 (2011), pp 239-254.
- Davis B, Di Giuseppe S, Zezza A (2017). Are African Households (Not) leaving agriculture? Patterns of households' income sources in rural Sub-Saharan Africa. *Food Policy*, 67 (2017), pp. 153–174.
- Demirbaş N, Niyaz ÖC, Daysal H (2017). Evaluation of Self-Sufficiency in Lentil Production in Turkey. *Journal of Agricultural Faculty of Gaziosmanpaşa University (JAFAG)*, (2017) 34 (3), 282-291.
- FAO (2012a). *Cadre de programmation pays (2012-2015)*.
- FAO (2012b). *FAO Statistical Yearbook 2012, World Food and Agriculture* <http://www.fao.org/> (Accessed to web: 5 March 2019 at 1:21).
- Fofana I, Goundan A, Domgho LVM (2014). Impact simulation of ECOWAS rice self sufficiency policy, IFPRI Discussion Paper 1405. Washington, DC: International Food Policy Research Institute, <http://ebrary.ifpri.org/cdm/ref/collection/p15738coll2/id/128894>.
- Hemavathi M, Prabakaran K (2018). ARIMA Model for Forecasting of Area, Production and Productivity of Rice and Its Growth Status in Thanjavur District of Tamil Nadu, India. *Int.J.Curr.Microbiol.App.Sci.* 7(02): 149-156. doi:<https://doi.org/10.20546/ijcmas.2018.702.019>
- Jacques AZ (2008). Etude économétrique de l'offre du riz local au Bénin à partir des données transversales; 87p.
- Kennedy P (2006). *Ekonometrikilavuzu, (çeviren Sarımeşeli M ve Açıkgöz Ş.)*, Gazikitepevi, 5.baskı, Ankara, 745 sayfa.
- LARES (2008). Analyse des politiques et stratégies mises en œuvre par l'état dans la filière riz depuis 2008; 22p.
- Laroche DP (2013). Food sovereignty and agricultural trade policy commitments: How much leeway do west African nations have? *Food Policy*, 38, 115–125.
- MAEP (2007). Analyse de la rentabilité économique de la chaîne de valeur ajoutée riz. Cotonou, Bénin.
- MAEP (2010). Diagnostic du secteur agricole de pays: dépenses publiques, Octobre 2010.
- Ohyver M, Pudjihastuti H (2018). Arima Model for Forecasting the Price of Medium Quality Rice to Anticipate Price Fluctuations. *Procedia Computer Science* 135 (2018) 707–711
- Okur, S (2009). “Parametrik Ve Parametrik Olmayan Basit Doğrusal Regresyon Analiz Yöntemlerinin Karşılaştırmalı Olarak İncelemesi” *Yüksek Lisans Tezi, Cukurova Üniversitesi, Adana*
- Özer, O O and İlkdoğan U (2013). Box-Jenkins Modeli Yardımıyla Dünya Pamuk Fiyatının Tahmini. *JOTAF/Tekirdağ Ziraat Fakültesi Dergisi* 10.2 (2013): 13-20.
- PNUD-IDH (2011). Rapport sur le développement humain 2011. [http://hdr.undp.org/sites/default/files/hdr\\_2011\\_fr\\_complete.pdf](http://hdr.undp.org/sites/default/files/hdr_2011_fr_complete.pdf) (accessed 30 June 2018, 10:12).
- Rahman NMF, Hasan MM, Hossain MI, Baten MA, Hosen S, Ali MA, Kabir MS (2016). Forecasting Aus Rice Area and Production in Bangladesh using Box-Jenkins Approach.
- Saito K, Dieng I, Toure AA, Somado EA, Wopereis MCS (2015). Rice yield growth analysis for 24 African countries over 1960–2012. *Global Food Security*, 5, 62–69.
- Seck PA, Diagne A, Mohanty S, Wopereis MCS (2012). Crops that feed the world 7: rice. *Food Security* 4, 7–24.
- Seck PA, Toure AA, Coulibaly JY, Diagne A, Wopereis MCS (2013). Africa's rice economy before and after the 2008 rice crisis. In M. C. S. Wopereis, D. E. Johnson, N. Ahmadi, E. Tollens, & A. Jalloh (Eds.), *Realizing Africa's rice promise* (pp. 24–34). Wallingford: CABI Publishing.
- Sharma PK, Dwivedi S, Ali L, Arora RK (2018). Forecasting Maize Production in India using ARIMA Model. *Agro Economist - An International Journal*. AE: 5(1): 01-06, June 2018. DOI: 10.30954/2394-8159.01.2018.1.
- Suleman N, Sarpong S (2012). Forecasting Milled Rice Production in Ghana Using Box-Jenkins Approach. *International Journal of Agricultural Management & Development*, 2(2): 79-84, June, 2012.
- Theil H (1958), *Economic Forecasts and Policy*. Amsterdam: North Holland. pp 31-42.
- Thirtle C, Lin L, Piesse J (2003). The Impact of Research-Led Agricultural Productivity Growth on Poverty Reduction in Africa, Asia and Latin America. *World Development*, 31(12), 1959-1975. doi: 10.1016/j.worlddev.2003.07.001.
- USDA (2016). PSD Online home Custom query. (<http://apps.fas.usda.gov/psdonline/>).
- Van Oort PAJ, Saito K, Tanaka A, Amovin-Assagba E, Van Bussel LGJ, van Wart J, de Groot H, van Ittersum MK, Cassman KG, Wopereis M C S (2015). Assessment of rice self-sufficiency in 2025 in eight African countries.
- Vergil H and Ozkan F (2007). “Döviz Kurları Öngörüsünde Parasal Model ve Arima Modelleri”, *Kocaeli Üniversitesi Sosyal Bilimler Enstitüsü Dergisi* 13(1): 211[231].