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# ONLINE PRESENTATIONS

## 03.09.2022 / Hall-1 / Session-2

| | |
|---|---|
| Ankara Local Time | Meeting ID: 839 6259 8369 |
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**HEAD OF SESSION: John Chiwuzulum Odozi**

| AUTHORS | AFFILIATION | TOPIC TITLE |
|---|---|---|
| Isa Diadia Alhassan<br>Lawal Adamu | *Department of Mathematics, Federal University of Technology, Minna, Nigeria* | APPLICATION OF GREY-MARKOV GMM (1, 1) MODEL FOR FORECASTING NIGERIA ANNUAL SOYBEAN PRODUCTION |
| Oyefeso, B.O.<br>Udu, G.O. | *University of Ibadan, Ibadan, Nigeria* | EFFECT OF HEAT TREATMENTS ON PROXIMATE COMPOSITION OF SWEET POTATO TUBERS |
| Okonkwo, H.O<br>Omokhua, G. E<br>Chima U. D | *Swamp Forest Research station, Forestry Research Institute of Nigeria, Onne<br>Dept of Forestry and Wildlife Management, Faculty of Agriculture, University of Port Harcourt* | SIZE AT REPRODUCTIVE MATURITY ONSET IN GARCINIA KOLA (HECKEL) |
| Micheal Taiwo AYANKOSO<br>Azeez Olanrewaju YUSUF | *Adekunle Ajasin University. Federal University of Agriculture<br>Federal University of Agriculture* | IMPACT OF UREA-SULPHUR MIXTURE ADDITIVE IN SWEET POTATO PEEL UTILIZATION ON PERFORMANCE, HAEMATOLOGY AND BLOOD CHEMISTRY OF WEST AFRICAN DWARF SHEEP |
| Mujahid ALI | *Water Management Research Farm, Renala Khurd, Okara, Pakistan* | GUAVA PRUNING PRACTICES-AN OVERVIEW |
| John Chiwuzulum Odozi | *Ajayi Crowther University, Oyo Town, Nigeria* | SOURCES OF AGRICULTURAL LABOUR PRODUCTIVITY GAP IN RURAL NIGERIA: A MICRO-LEVEL DECOMPOSITION |
| LAABAS S.<br>Boukirat D.<br>Chaker H.<br>Berber F. | *University of Ahmed Ben Yahia el Wancharissi, Tissemsilt, Algeria* | EFFECT OF TREATING PEA SEEDS (PISUM SATIVUM) WITH FUNGICIDE ON THE ESTABLISHMENT OF SYMBIOSIS |

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# APPLICATION OF GREY-MARKOV GMM (1, 1) MODEL FOR FORECASTING NIGERIA ANNUAL SOYBEAN PRODUCTION

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## ABSTRACT

Providing reliable and dependable information, using a scientifically proven technique to the farmers, other Agricultural stakeholders and Government as a guide for better planning and sustainable Soybean production in Nigeria is the main focus of this paper. Many leguminous crops provide some protein, but Soybean is the only available crop that provides an inexpensive and high quality source of protein comparable to meat, poultry and eggs. A Grey-Markov model was developed to forecast the Nigeria annual Soybean production. The data used in this paper was collected from the United State Department of Agriculture (USDA) for a period of eleven years (2010- 2020). The result revealed a very high percentage forecasting accuracy of 97.7%, thus a high forecasting ability. This shows a reliable and dependable model. The results could assist the farmers, other agricultural stakeholders and government to plan and make better decisions aimed at reducing poverty and ensuring food security.

**Keywords:** Agriculture, Farmers, Government, Soybeans, Production, Nigeria, Forecasting, Grey-Markov.

The rapid growth in the poultry sector in the past five years has also increased demand for Soybean meal in Nigeria. It is believed that Soybean production will increase as more farmers become aware of the potentials of the crop, not only for cash or food, but also for soil fertility improvement and stiga control. Soybean is a source of vegetable oil in International markets and its oil is found to be 85% unsaturated and cholesterol-free. Soybean also consists of more than 36% protein, 30% carbohydrates, and excellent amounts of dietary fiber, Vitamins, and minerals. Malnutrition, particularly protein deficit, is prevalent in many parts of Africa as animal protein is too expensive for most populations. Many leguminous crops provide some protein, but Soybean is the only available crop that provides an inexpensive and high quality source of protein comparable to meat, poultry and eggs. A by-product from the Soybean oil production (Soybean cake) is used as a high-protein animal feed in many countries, including Nigeria. It also improves soil fertility by adding nitrogen from the atmosphere. This is a major benefit in African farming systems, where the soil have become exhausted by the need to produce more food for increasing populations, and where fertilizers are hardly available and are expensive for farmers (IITA,2010.USDA, 2012).

The market for Soybean in Nigeria is growing very fast with opportunities for improving the income of farmers. Currently, SALMA oil mills in Kano, Grand cereals in Jos, ECWA feeds in Jos, AFCOT oil seed processors, Ngurore in Adamawa state, and PS Mandrides in Kano.

In view of the above, national and international bodies have developed interest in promoting Soybean production for household and to ensure food security and poverty alleviation. Some of these efforts have been channeled through biological and agronomic researches into the development of high-yielding varieties along with best cultural practices.

Thus, providing a scientific-proven prediction/forecasting technique to determine the production outputs of Soybean grains at high level of precision as information for stakeholders such as farmers, commodity traders and government officials for planning and decision-making purposes, is the trust of this paper.

This paper considers the use of Grey-Markov GM (1, 1) model to forecast the production outputs of Soybean crops. The Grey-Markov model is proposed based on the advantages of both methods which adopts the GM (1, 1) to study development regulation of data sequence and uses Markov chain model to study vibrating irregularities of data sequence. Both Grey GM (1, 1) and Grey-Markov models have been successfully applied in various areas of agricultural researches.

GM(1, 1) forecasting model is a viable and powerful mathematical tool because of its ability to use small size and make short and long time forecasting with minimal error (Jian-Yi and Ying, 2014; Wei and Jian-Min, 2013; Yong and Yang,). Grey-Markov is a combination of the Grey GM (1, 1) model and Markov chain. The Grey system GM (1, 1) and Grey-Markov models both have proven track record of high level of accuracy in forecasting (Li Q et al., 2007; Mao and Sun, 2011; Yong et al., 2016; Xin et al., 2018).

**Materials and Methods**

**Developing a Grey GM (1, 1) Model for Forecasting Soybean Production Yields**

The grey GM (1, 1) model is established by making use of discrete data series to form a continuous differential equation by successive addition of original data series (raw data), from first in accumulating generation operation (AGO). The solution of the differential equation is then used to perform forecasting (Li. Q et al, 2007). The procedure is carried out step by step as follow:

Let the raw data series be represented by $X^{(0)}(k)$, k = 1, 2, 3,....,n, That is, $X^{(0)}(k) \geq 0$.

The raw data series can be expressed as:

$$X^{(0)}(k)=(x^{(0)}(1),x^{(0)}(2),x^{(0)}(3),....,x^{(0)}(n)) \tag{1}$$

Let also the accumulated generating operation (AGO) be represented as $X^{(1)}(k)$. Which is derived by successive addition, from first series, of the original data series.

That is,

$$X^{(1)}(k) = \{x^{(1)}(1), x^{(1)}(2),....,x^{(1)}(n) \} \text{ and} \tag{2}$$

$$X^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), k = 1, 2, 3,....,n \tag{3}$$

Where $X^{(1)}(k)$ is the accumulating generating operation on $X^{(0)}(k)$, denoted as (AGO).

By differentiating equation (3) with respect to t, a whitened differential equation is obtained as:

$$\frac{dX^{(1)}}{dt} + aX^{(1)} = b \tag{4}$$

Where " a " and " b " are parameters to be identified. " a " is called grey developing coefficient, while "b" is the grey input or grey effect (Lawal Adamu *et al*, 2021).The difference form of equation (4) is given as:

$$X^{(0)}(k) + aX^{(1)}(k) = b \tag{5}$$

Equation (5) represents the original form of the GM (1, 1) model. The symbol GM (1, 1) stands for first order grey model in one variable.

The solution of equation (4) is given as:

$$\hat{X}^{(1)}(k+1) = \left(X^{(0)}(1) - \frac{b}{a}\right)e^{-ak} + \frac{b}{a} \tag{6}$$

Equation (6) is called the time response function, while the parameters "a" and "b" are estimated using Least Square Method, given as:

$$\begin{bmatrix} a \\ b \end{bmatrix} = \{B^T B\}^{-1} B^T Y \tag{7}$$

$$\text{Where } B = \begin{bmatrix} -Z^{(1)}(2) & 1 \\ -Z^{(1)}(3) & 1 \\ -Z^{(1)}(4) & 1 \\ \vdots & \vdots \\ -Z^{(1)}(n) & 1 \end{bmatrix} \tag{8}$$

$$Z^{(1)}(k) = \frac{x^{(1)}(k) + x^{(1)}(k-1)}{2}, \; k = 2, 3, 4 \ldots\ldots, n \tag{9}$$

$$\text{And } Y = [x^{(0)}(2), X^{(0)}(3), X^{(0)}(4), \ldots\ldots, X^{(0)}(n)]^T \tag{10}$$

The grey simulated/predicted values are obtained by an operation on equation (6), given as:

$$\hat{X}^{(0)}(k+1) = \hat{X}^{(1)}(k+1) - \hat{X}^{(1)}(k)\left(1 - e^{a}\right)\{x^{(0)}(1) - \frac{b}{a}\Big) e^{-ak} \tag{11}$$

The difference between the exact values, equation (1) and the grey simulated values, equation (11) gives the residual error of the forecast.

That is,

$$E^{(0)}(k) = X^{(0)}(k) - \hat{X}^{(0)}(k) \text{ and} \tag{12}$$

$$E^{(0)}k) = \{E^{(0)}(1), E^{(0)}(2), \ldots\ldots, E^{(0)}(n)\} \tag{13}$$

**Forecasting Accuracy Test**

Numerous methods exist for judging forecasting model accuracy, and no single recognised inspection method exists for forecasting ability. The Mean Absolute Percentage Error (MAPE) is often used to measure forecasting accuracy and adopted for this paper. MAPE is a measure of accuracy in a fitted time series value in statistics, specifically trending. It usually expresses accuracy in percentage. The smaller the MAPE, the better the forecasting ability of the model applied.

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i-\hat{Y}_i}{Y_i}\right| \text{ x } 100\% \qquad (14)$$

Where n is the forecasting number of steps or the number of forecasting samples

$Y_i$ is the original data series

$\tilde{Y}_i$ is the grey model forecasted value (Xin Z *et al.*, 2018)

Lewis (1982) evaluated the MAPE forecasting accuracy of the models by dividing the forecasting ability into four grades classified as follow:

**Table1: Forecasting Accuracy Test Table**

| MAPE | Prediction Accuracy |
|---|---|
| < 10% | High |
| 10%--20% | Good |
| 20%--50% | Feasible |
| >50% | Low |

**Developing Grey-Markov (GMM) Model for Forecasting Nigeria Annual Soybean Production Yields**

The Grey-Markov model (GMM) is an extension of grey GM (1, 1) model, to further reduce the forecasting errors associated with grey system. In grey model, the problems of poor fitting accuracy in percentage. The smaller the MAPE, the better the forecasting ability of the model applied.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right| \times 100\% \qquad (14)$$

Where n is the forecasting number of steps or the number of forecasting samples

$Y_i$ is the original data series

$\hat{Y}_i$ is the grey model forecasted value (Xin Z *et al.*, 2018)

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**Developing Grey-Markov (GMM) Model for Forecasting Nigeria Annual Soybean Production Yields**

The Grey-Markov model (GMM) is an extension of grey GM (1, 1) model, to further reduce the forecasting errors associated with grey system. In grey model, the problems of poor fitting degree and low forecasting accuracy may emerge when the range of original data is too large. However, these problems can be well resolved by adopting Markov chain model which will be used to narrow down the forecasting interval and improve the forecasting accuracy. Markov stochastic process improves these limitations of grey model because it reflects the stochastic volatility impact on elements by determining the transfer law of states (Ducan et al, 1998).

The first step in building the model GMM is to divide the relative percentage errors into q states where each state satisfies the probability principle and is defined as $R_1, R_2, R_3, \ldots R_q$. The next step is to construct the transition matrix by determining the transitions from state $R_i$ to $R_j$ which results in the formation of transition matrix P.

---

$$p(1) = \begin{bmatrix} P_{(11)}^{(1)} & P_{(12)}^{(1)} & \cdots & P_{(1q)}^{(1)} \\ P_{(21)}^{(1)} & P_{(22)}^{(1)} & \cdots & P_{(2q)}^{(1)} \\ \vdots & \vdots & \cdots & \vdots \\ P_{(q1)}^{(1)} & P_{(q2)}^{(1)} & \cdots & P_{(qq)}^{(1)} \end{bmatrix} \quad (15)$$

$$p(m) = \begin{bmatrix} P_{(11)}^{(m)} & P_{(12)}^{(m)} & \cdots & P_{(1q)}^{(m)} \\ P_{(21)}^{m} & P_{(22)}^{(m)} & \cdots & P_{(2q)}^{(m)} \\ \vdots & \vdots & \cdots & \vdots \\ P_{(q1)}^{(m)} & P_{(q2)}^{(m)} & \cdots & P_{(qq)}^{(m)} \end{bmatrix} \quad (16$$

$P_{ij}^{(m)} = \frac{M_{ij}^{(m)}}{m_i}$, (i, j, = 1, 2, 3, ...L) *and* $M_{ij}^{(m)}$ stands for the transition from $R_i$ to $R_j$ in m-steps and $M_j$ is the number of state $R_j$.

Next is to configure the relative percentage errors by letting the interval median in $[R_{i-}, R_{i+}]$ be the residual error forecasting value given as:

$$\hat{e} = \frac{1}{2}[R_{i-} + R_{i+}] \quad (17)$$

So, the Grey-Markov model is obtained as:

$$\hat{Y}(k+1) = [1+\hat{e}]\hat{X}^{(0)}(k+1) \quad (18)$$

Putting equation (11) into equation (18), the resulting equation is:

$$\hat{Y}(k+1) = \left[1 + \frac{1}{2}(R_{i-} + R_{j+}\right]\hat{X}^{(0)}(k+1) \quad (19)$$

(19) is the Grey-Markov model equation used to obtain the simulated values of soybean production.

## Results and Discussion

### Application of Grey GM (1, 1) Model for Forecasting Nigeria Annual Soybean Production

The data used for this paper was collected from the United State Department of Agriculture (USDA) for a period of eleven years (2010-2020) as presented in table 2 below.

**Table 2:** Nigeria Annual Soybean Production value from 2010 to 2020

| Year of production | Soybean production ('000 metric tons) |
|---|---|
| 2010 | 145,000 |
| 2011 | 180,000 |
| 2012 | 200,000 |
| 2013 | 220,000 |
| 2014 | 240,000 |
| 2015 | 350,000 |
| 2016 | 420,000 |
| 2017 | 450,000 |
| 2018 | 465,000 |
| 2019 | 465,000 |
| 2020 | 465,000 |

Source: United State Department of Agriculture (USDA) Report 2021

Applying equation (1) to table 2, equation (20) is obtained:

$$X^{(0)}(k) = (145, 180, 200, 220, 240, 350, 420, 450, 465, 465, 465) \quad (20)$$

K = 1, 2, 3, ...11

The accumulated generating operation (AGO) of equation (20) is obtained using equation (2) such that:

$$X^{(1)}(k) = (145, 325, 525, 745, 985, 1335, 1755, 2205, 2670, 3135, 3600) \quad (21)$$

Also, using equation (9), equation (22) is obtained as:

$$Z^{(1)}(k) = (235, 425, 635, 865, 1160, 1545, 1980, 2437.5, 2902.5, 3367.5) \quad (22)$$

From equation (7),

$$\begin{bmatrix} a \\ b \end{bmatrix} = [B^T B]^{-1} B^T Y$$

$$Y = \begin{bmatrix} 180 \\ 200 \\ 220 \\ 240 \\ 350 \\ 420 \\ 450 \\ 465 \\ 465 \\ 465 \end{bmatrix} \quad (23)$$

$$B = \begin{bmatrix} -235 & 1 \\ -425 & 1 \\ -635 & 1 \\ -865 & 1 \\ -1160 & 1 \\ -1545 & 1 \\ -1980 & 1 \\ -2437.5 & 1 \\ -2902.5 & 1 \\ -3367.5 & 1 \end{bmatrix} \tag{24}$$

$$B^T = \begin{bmatrix} -235 & -425 & -635 & -865 & -1160 & -1545 & .. & .. & .. & -3367.5 \\ 1 & 1 & 1 & 1 & 1 & 1 & .. & .. & .. & 1 \end{bmatrix} \tag{25}$$

Recall equation (7) and letting C = $[B^T B]$ such that $C^{-1} = [B^T B]^{-1}$ (26)

Also, let D = $B^T Y$ (27)

Such that:

$$\begin{bmatrix} a \\ b \end{bmatrix} = C^{-1} D \tag{28}$$

Using equations (26), (27) and (28), we have:

$$\begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} -0.103798 \\ 184.042879 \end{bmatrix} \tag{29}$$

Here, a = -0.103798 and b = 184.042879

Substituting for 'a', 'b' and $X^{(0)}(1)$ into equation (6), we obtain equation (30) below:

$\hat{X}^{(1)}(k)$= (145, 354.793, 587.533, 845.729, 1132.166, 1449.931, 1802.453, 2193.533, 2627.387, 3108.695, 3642.646) (30)

And $\hat{X}^{(0)}$ = (145,000, 209,793, 232,740, 258,196 286,437 317,765, 352,522, 433,854, 482,308, 533,951) (31)

This is the grey simulated values of Soybean production from 2010 to 2020 as presented in Table 3.

**Table 3: Comparison of Actual and Grey simulated values for Nigeria Soybean Production from 2010 to 2020**

| S/N | Year of Production | Actual Soybean Production ('000 tons) | Grey simulated Soybean production('000 tons) | Residual Error | Relative error (%) |
|---|---|---|---|---|---|
| 1 | 2010 | 145 | 145 | 0 | 0 |
| 2 | 2011 | 180 | 209.793 | -29.793 | -16.55 |
| 3 | 2012 | 200 | 232.740 | -32.740 | -16.37 |
| 4 | 2013 | 220 | 258.196 | -38.196 | -17.36 |
| 5 | 2014 | 240 | 286.437 | -46.439 | -19.35 |
| 6 | 2015 | 350 | 317.765 | 32.235 | 9.21 |
| 7 | 2016 | 420 | 352.522 | 67.478 | 16.07 |
| 8 | 2017 | 450 | 391.080 | 58.920 | 13.09 |
| 9 | 2018 | 465 | 433.854 | 31.146 | 6.70 |
| 10 | 2019 | 465 | 481.308 | -16.308 | -3.51 |
| 11 | 2020 | 465 | 533.951 | -68.951, | -14.83 |

Using equation (12) and table 3, it is observed that the mean absolute percentage error (MAPE) is obtained as:

$\text{MAPE} = \frac{1}{11}(133.04) = 12.09\%$ and so the forecasting ability of the model is given as:

Forecasting ability of the Grey model = 100% - 12.09% = 87.91% ≈ 88%.

We begin by dividing the relative error percentage into three states as shown below:

**Table 4: State Division for the Error States of Soybean production**

| STATE | $E_1(\%)$ | $E_2(\%)$ | $E_3(\%)$ |
|---|---|---|---|
| ERROR RANGE | -19.35 ~ -7.54 | -7.54 ~ 4.27 | 4.27 ~ 16.07 |

By assigning the error states of table 4 to table 5, another table 6 is obtained as follow:

**Table 5: The Error States for Grey Simulated Values of Soybean Production from 2010 to 2020.**

| N/S | Year of Production | Actual values of Soybean Production ('000) | Grey Simulated values of Soybean Production('000) | Relative Error (%) | Error State |
|---|---|---|---|---|---|
| 1 | 2010 | 145 | 145 | 0 | $E_2$ |
| 2 | 2011 | 180 | 209.793 | -16.55 | $E_1$ |
| 3 | 2012 | 200 | 232.740 | -16.37 | $E_1$ |
| 4 | 2013 | 220 | 258.196 | -17.36 | $E_1$ |
| 5 | 2014 | 240 | 286.437 | -19.35 | $E_1$ |
| 6 | 2015 | 350 | 317.765 | 9.21 | $E_3$ |
| 7 | 2016 | 420 | 352.522 | 16.07 | $E_3$ |
| 8 | 2017 | 450 | 391.080 | 13.09 | $E_3$ |

| | | | | | |
|---|---|---|---|---|---|
| 9 | 2018 | 465 | 433.854 | 6.7 | $E_3$ |
| 10 | 2019 | 465 | 481.359 | -3.51 | $E_2$ |
| 11 | 2020 | 465 | 533.951 | -14.83 | $E_1$ |

Using equation (19) and table 5, the Grey-Markov simulated values of Nigeria annual Soybean production from 2010 to 2020 are obtained as follow:

$$(1) = [1 + ½(-7.65 + 4.15)] \times 145{,}000 = 142{,}629 \tag{32}$$

K = 1

$$\hat{Y}(2) = [1 + ½(-19.45 - 7.65)] \times 209{,}840 = 181{,}607 \tag{33}$$

K = 2

$$\hat{Y}(3) = [1 + ½(-19.45 - 7.65)] \times 232{,}840 = 201{,}471 \tag{34}$$

K = 3

$$\hat{Y}(4) = [1 + ½(-19.45 - 7.65)] \times 258360 = 223{,}507 \tag{35}$$

K = 4

$$\hat{Y}(5) = [1 + ½(-19.45 - 7.65)] \times 286670 = 247{,}954 \tag{36}$$

K = 5

$$\hat{Y}(6) = [1 + ½(4.15 + 15.96)] \times 318100 = 350{,}098 \tag{37}$$

K = 6

$$\hat{Y}(7) = [1 + ½(4.15 + 15.96)] \times 352960 = 388{,}391 \tag{38}$$

K = 7

$$\hat{Y}(8) = [1 + ½(4.15 + 15.96)] \times 391640 = 430{,}872 \tag{39}$$

K = 8

$$\hat{Y}(9) = [1 + ½(4.15 + 15.96)] \times 434560 = 477{,}999 \tag{40}$$

K = 9

$$\hat{Y}(10) = [1 + ½(-7.65 + 4.15)] \times 482{,}200 = 473{,}489 \tag{41}$$

$K = 10$

$$\hat{Y}(11) = [1 + ½(-19.45 - 7.65)] \times 535200 = 462,161 \tag{42}$$

**Table 6: Comparison of the Actual and Grey-Markov Simulated Values of Soybean Production from 2010 to 2021**

| S/N | Year of Production | Actual Soybean Production ('000 Tons) | Grey-Markov Simulated values of Soybean production('000 tons) | Residual Error | Relative Error (%) |
|---|---|---|---|---|---|
| 1 | 2010 | 145,000 | 142,629 | 2371 | 1.64 |
| 2 | 2011 | 180,000 | 181,607 | -1607 | -0.89 |
| 3 | 2012 | 200,000 | 201,471 | -1471 | -0.74 |
| 4 | 2013 | 220,000 | 223,507 | -3507 | -1.59 |
| 5 | 2014 | 240,000 | 247,954 | -7954 | -3.31 |
| 6 | 2015 | 350,000 | 350,098 | -098 | -0.03 |
| 7 | 2016 | 420,000 | 388,391 | 31609 | 7.53 |
| 8 | 2017 | 450,000 | 430,872 | 19128 | 4.25 |
| 9 | 2018 | 465,000 | 477,999 | -12999 | -2.8 |
| 10 | 2019 | 465,000 | 473,489 | --8489 | -1.83 |
| 11 | 2020 | 465,000 | 462,161 | 2,839 | 0.61 |

Applying equation (14) to (6), MAPE is obtained as follows: MAPE = 1/11 × 25.22% = 2.29%.

This is the forecasting error percentage and the forecasting accuracy of 97.7%. The figure below shows the comparison between the actual Soybean production values, and the simulated values of soybean production using Grey GM (1, 1) and Grey-Markov models.

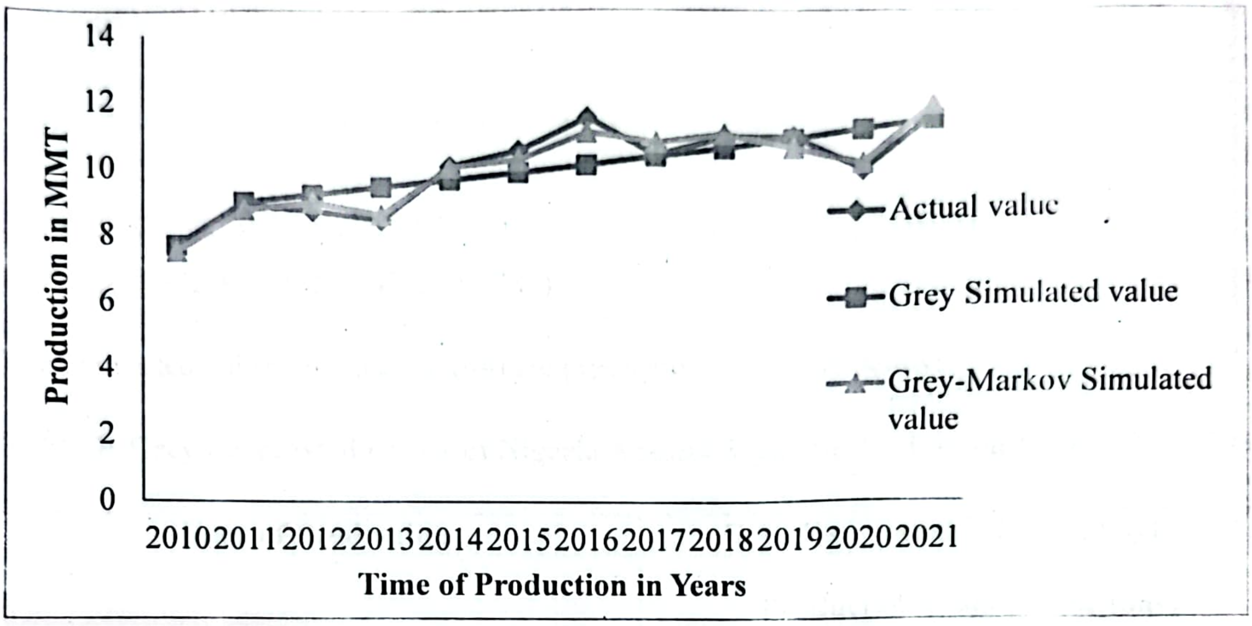


Fig. 1: Comparison of the Actual Soybean Production Values, and the Grey and Grey-Markov simulated values of Soybean Production from 2010 to 2020.

**Grey Forecasted values for Nigeria Annual Soybean Production from 2021 to 2033**

Similarly, to forecast the Nigeria Annual Soybean Production from 2021 to 2033, equation (19) is evaluated for values of k = 11, 12, 13,...., 23. So the accumulated generating operation ($\hat{X}^{(1)}$), is obtained as follow:

$$X^{(1)} = (4240.999, 4899.769, 5630.739, 6441.825, 7341.805, 8340.424, 9448.493, 10678.005, 12042.274, 13556.066, 15235.771, 17099.572, 19167.647) \quad (43)$$

The next step is the computation of the forecasting values for Nigeria annual Soybean production from 2021 to 2033 using equation (19) as follow:

Applying $\hat{X}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{b}{a}\right) e^{-ak} - \frac{b}{a}$ and the equation, $\hat{X}^{(0)}(k) = \hat{X}^{(1)}(k) - \hat{X}^{(1)}(K-1)$, the following results are obtained:

$\hat{X}^{(1)}(k)$ = (4235, 4892.142, 5621.16, 6429.916, 7327.13, 8322.479, 9426.695, 10651.686, 12010.662. 13518.278, 15190.792,

17046.239, 19104.628), for values of k = 11, 12, 13, ...23 (44)

$\hat{X}^{(0)}$ = (592.354, 657.142, 729.018, 808.756, 897.214, 995.349, 1104.216, 1224.991 1358.976. 1507.616, 1672.514, 1855.447, 2058.389) (45)

The forecasted values of equation (44) are presented in the table below:

**Table 7: Grey Forecasted values of Nigeria Annual Soybean Production from 2021 to 2033**

| Year of Production | Grey Forecasted values of Soybean Production ('000 metric tons) |
|---|---|
| 2021 | 593,700 |
| 2022 | 658,770 |
| 2023 | 730,970 |
| 2024 | 811,086 |
| 2025 | 899,980 |
| 2026 | 998,619 |
| 2027 | 1,108,069 |
| 2028 | 1,229,512 |
| 2029 | 1,364,269 |
| 2030 | 1,513,792 |
| 2031 | 1,679,705 |

| | |
|---|---|
| 2032 | 1,863,801 |
| 2033 | 2,068,075 |

**Grey-Markov Forecasted Values of Nigeria Annual Soybean Production from 2021 to 2033**

To achieve this, the error states for 2021 to 2033 is to be obtained using equations (46) to (58) and information in Table 5 and then use equation (19) and the error states to make forecasting for the years, 2021 to 2033, as presented in Table 7

From Table 5, the transition probability matrix can be constructed using equation (15)

$$p^{(1)} = \begin{bmatrix} 0.75 & 0 & 0.25 \\ 1 & 0 & 0 \\ 0 & 0.25 & 0.75 \end{bmatrix} \tag{46}$$

Performing two steps, three steps, four steps and up to thirteenth steps, the transition probability matrix is calculated using equation (3.16). They are obtained respectively as follow:

$$p^{(2)} = \begin{bmatrix} 0.563 & 0.063 & 0.375 \\ 0.75 & 0 & 0.25 \\ 0.25 & 0.188 & 0.563 \end{bmatrix} \tag{47}$$

$$p^{(3)} = \begin{bmatrix} 0.485 & 0.094 & 0.422 \\ 0.563 & 0.063 & 0.375 \\ 0.375 & 0.141 & 0.485 \end{bmatrix} \tag{48}$$

$$p^{(4)} = \begin{bmatrix} 0.458 & 0.106 & 0.438 \\ 0.485 & 0.094 & 0.422 \\ 0.422 & 0.122 & 0.458 \end{bmatrix} \tag{49}$$

$$p^{(5)} = \begin{bmatrix} 0.449 & 0.110 & 0.443 \\ 0.458 & 0.106 & 0.438 \\ 0.438 & 0.115 & 0.449 \end{bmatrix} \tag{50}$$

$$p^{(6)} = \begin{bmatrix} 0.446 & 0.111 & 0.445 \\ 0.449 & 0.110 & 0.443 \\ 0.443 & 0.113 & 0.446 \end{bmatrix}. \tag{51}$$

$$p^{(7)} = \begin{bmatrix} 0.445 & 0.111 & 0.445 \\ 0.446 & 0.111 & 0.445 \\ 0.445 & 0.112 & 0.445 \end{bmatrix} \tag{52}$$

$$P^{(8)} = \begin{bmatrix} 0.445 & 0.111 & 0.445 \\ 0.445 & 0.111 & 0.445 \\ 0.445 & 0.112 & 0.445 \end{bmatrix} \quad (53)$$

$$P^{(9)} = \begin{bmatrix} 0.445 & 0.111 & 0.445 \\ 0.445 & 0.111 & 0.445 \\ 0.445 & 0.112 & 0.445 \end{bmatrix} \quad (54)$$

$$P^{(10)} = \begin{bmatrix} 0.445 & 0.111 & 0.445 \\ 0.445 & 0.111 & 0.445 \\ 0.445 & 0.112 & 0.445 \end{bmatrix} \quad (55)$$

$$P^{(11)} = \begin{bmatrix} 0.445 & 0.111 & 0.445 \\ 0.445 & 0.111 & 0.445 \\ 0.445 & 0.112 & 0.445 \end{bmatrix} \quad (56)$$

$$P^{(12)} = \begin{bmatrix} 0.445 & 0.111 & 0.445 \\ 0.445 & 0.111 & 0.445 \\ 0.445 & 0.112 & 0.445 \end{bmatrix} \quad (57)$$

$$P^{(13)} = \begin{bmatrix} 0.445 & 0.111 & 0.445 \\ 0.445 & 0.111 & 0.445 \\ 0.445 & 0.112 & 0.445 \end{bmatrix} \quad (58)$$

The next step is to find the error states of each year from 2021 to 2033.From Table 10, the error state for 2020 is $E_1$, and this implies that the initial state vector for the Grey-Markov forecasting is:

$$V_0 = [1 \quad 0 \quad 0] \quad (59)$$

The error state for the year, 2021 is obtained by multiplying equation (59) and equation (46)

$$V_1 = [1 \quad 0 \quad 0]\begin{bmatrix} 0.75 & 0 & 0.25 \\ 1 & 0 & 0 \\ 0 & 0.25 & 0.75 \end{bmatrix} = [0.75 \quad 0 \quad 0.25] = E_1 = 2021 \quad (60)$$

The error state for the year, 2022 is obtained, multiplying equation (60) by equation (47)

$$V_2 = [0.75 \quad 0 \quad 0.25]\begin{bmatrix} 0.563 & 0.063 & 0.375 \\ 0.75 & 0 & 0.250 \\ 0.25 & 0.188 & 0.563 \end{bmatrix} = [0.485 \quad 0.094 \quad 0.422] = E_1 \quad 2022 \tag{61}$$

Similarly, the error states for the years 2023 – 2033 are obtained as follow:

$$V_3 = E_1 = 2023 \tag{62}$$

$$V_4 = E_3 = 2024 \tag{63}$$

$$V_5 = E_1 = 2025 \tag{64}$$

$$V_6 = E_3 = 2026 \tag{65}$$

$$V_7 = E_1 = 2027 \tag{66}$$

And error states for 2028, 2029, 2030, 2031, 2032 and 2033 are $E_3, E_1, E_3, E_1, E_3$ *and* $E_1$.

Using equation (19) and the error states obtained for the respective years, the forecasted values of Soybean from 2021 to 2033 are estimated as follow:

For k = 11

$$\hat{Y}_{12}(2021) = [1 + ½(-19\text{-}45 - 65)] \times 593{,}700 = 513{,}254 \tag{67}$$

For k = 12

$$\hat{Y}_{13}(2022) = [1 + ½(-19.45 - 7.65)] \text{ X } 658{,}770 = 569{,}507 \tag{68}$$

For k = 13

$$\hat{Y}_{14}(2023) = [1 + ½(-19.45 - 7.65)] \text{ X } 730{,}970 = 631{,}924 \tag{69}$$

For k = 14

$$\hat{Y}_{15}(2024) = [1 + ½(4.15 + 15.96)] \text{ X } 811{,}086 = 892{,}641 \tag{70}$$

For k = 15

$$\hat{Y}_{16}(2025) = [1 + \tfrac{1}{2}(-19.45 - 7.65)] \text{ X } 899{,}980 = 778{,}033 \quad (71)$$

For $k = 16$

$$\hat{Y}_{17}(2026) = [1 + \tfrac{1}{2}(4.15 + 15.96)] \text{ X } 998{,}619 = 1{,}099{,}030 \quad (72)$$

For $k = 17$

$$\hat{Y}_{18}(2027) = [1 + \tfrac{1}{2}(-19.45 - 7.65)] \text{ X } 1{,}108{,}069 = 957{,}926 \quad (73)$$

For $k = 18$

$$\hat{Y}_{19}(2028) = [1 + \tfrac{1}{2}(4.15 + 15.96)] \text{ X } 1{,}229{,}512 = 1{,}353{,}139 \quad (74)$$

For $k = 19$

$$\hat{Y}_{20}(2029) = [1 + \tfrac{1}{2}(-19.45 - 7.65)] \text{ X } 1{,}364{,}269 = 1{,}179{,}411 \quad (75)$$

For $k = 20$

$$\hat{Y}_{21}(2030) = [1 + \tfrac{1}{2}(4.15 + 15.96)] \text{ X } 1{,}513{,}792 = 1{,}666{,}004 \quad (76)$$

For $k = 21$

$$\hat{Y}_{22}(2031) = [1 + \tfrac{1}{2}(-19.45 - 7.65)] \text{ X } 1{,}679{,}705 = 1{,}452{,}105 \quad (77)$$

For $k = 22$

$$\hat{Y}_{23}(2032) = [1 + \tfrac{1}{2}(4.15 + 15.96)] \text{ X } 1{,}863{,}801 = 2{,}051{,}206 \quad (78)$$

For $k = 23$

$$\hat{Y}_{24}(2033) = [1 + \tfrac{1}{2}(-19.45 - 7.65)] \text{ X } 2{,}068{,}075 = 1{,}787{,}851 \quad (79)$$

These values are represented in the table 8 below:

**Table 8: Grey-Markov Model Forecasting the Annual Soybean Production from 2021 to 2033**

| S/N | Year of Production | Grey-Markov Forecasted Values of Soybean Production |
|---|---|---|
| 1 | 2021 | 513,254 |
| 2 | 2022 | 569,507 |
| 3 | 2023 | 631,924 |
| 4 | 2024 | 892,641 |
| 5 | 2025 | 778,033 |
| 6 | 2026 | 1,099,030 |
| 7 | 2027 | 957,926 |
| 8 | 2028 | 1,353,139 |
| 9 | 2029 | 1,179,411 |
| 10 | 2030 | 1,666,004 |
| 11 | 2031 | 1,452,105 |
| 12 | 2032 | 2,051,206 |
| 13 | 2033 | 1,787,851 |

## DISCUSSIONS

The table 3 and 7, and figure 1 above indicate a steady increase in the Annual production values of Soybean in Nigeria using Grey GM (1, 1) model. The annual production values of Soybean in Nigeria rose from 145,000 thousand metric tons in 2010, to 2,068,075 million metric tons in 2033 using Grey GM (1, 1) forecasting model as reflected in Tables 3 and 7. It is also noticed that the relative percentage errors which ranged from -19.45% to 15.96% gave a reasonable interpretation of the results. The mean absolute percentage error involved in the use of the grey model is 12%, thus giving a percentage accuracy of the model as 88%.

Good as the forecasting ability of the Grey GM (1, 1) may be, when the model combines with Markov chain model as Grey-Markov model, performed better than the individual Grey model as reflected in Tables 5 and 8, and figure 1. Tables 5 and 8 indicate a more realistic increase in volume of soybean production and closer to the actual values of Annual Soybean production from 142,460 thousand metric tons in 2010 to 462,680 thousand metric tons, which validates the steady rise in the forecasted values of annual Soybean production from 2021 to 2033 even though, there were fluctuations. The percentage error which ranged from -3.31% to 7.53% gave a more reasonable result. The mean absolute percentage error of 2.3% involved in the use of Grey-Markov model gave a percentage accuracy of the model as 97.7%, thus indicating the reliability and dependability of Grey-Markov model.

## CONCLUSION

Providing adequate, reliable and dependable information that will ensure increase in government funding to agriculture, selection of high yielding Soybean varieties, and increasing agricultural linkage between farmers and research institutes are important factors needed to increase the yield and production of Soybean in future. This research work applied Grey system GM (1, 1) and Grey-Markov (GMM) models to forecast Nigeria annual Soybean production with precise forecasting and high forecasting accuracy. The two models have very good forecasting abilities even though, Grey-Markov model performs better than the Grey GM (1, 1) when applied singularly or individually. Grey-Markov simulated values of Soybean production are closer to the actual values of Soybean than the individual Grey GM (1, 1) model. The results from the two models show that the error percentages are quite low, thus it can be concluded that the models have high forecasting validity and accuracy, and clearly viable and dependable for forecasting crops production yields.

## Recommendation

Although government over the years have developed interest in promoting maize and soybean production for households, food security and poverty alleviation through programs and interventions, such as the CBN's Anchor Borrower's Schemes and IITA's Business Incubation Program (BIP), to resolve the challenges of low yield or poor output, it appears insufficient due largely to lack of adequate and reliable information available to agricultural stakeholders. The following recommendations are proffered:

The following recommendations are proffered:

1. The results from this models could offer a valuable reference for the government in drafting relevant policies for import and export activities, and for better planning and sustainable crops production in the country
2. The results from the models should be adopted by the agriculture sector to plan ahead of time to avoid shortfall in production yield particularly, when it is predicted.
3. From the results of the study, the fluctuations in the simulated and forecasted values of maize and soybean production from 2022 to 2033 could be used to offer constructive advice to government, to plan ahead of time, with regards to import and export in the event of shortfall or surplus for sustainable food security in the country.
4. Nigeria needs to intensify efforts already in place, like Anchor Borrower Scheme, to increase the volume of both maize and soybean production outputs in order to close the demand gap of (2 - 4) million metric tons, particularly maize production

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