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Probabilistic Insights and Uncertainty in Advanced Time-Series Forecasting Models for Ginger Supply Response

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ABSTRACT

Despite the increasing demand and growth potential of Nigeria's ginger production, the country has yet to fully harness the economic benefits of expanding value addition and market diversification. This study aims to advance ginger supply forecasting by employing cutting-edge time-series techniques to model and predict future ginger production while emphasizing credibility through uncertainty and probability estimates. Cointegration analysis and the Vector Error Correction Model (VECM) were utilized to model the supply response, while Exponential Smoothing (ETS), ARIMA, and Facebook Prophet models were employed to forecast ginger production over a 10-year horizon. The results revealed seven cointegrating relationships, with all predictors being highly significant. Notably, disease prevalence and input usage had the highest long-run elasticities, at -93.96 and 15.74, respectively, while inflation was significant in the short run. The forecast results indicate a high probability of increased production, albeit with greater uncertainty in the long term. Performance evaluation showed that the ARIMA (0,1,0) model outperformed other models with a Mean Absolute Scaled Error (MASE) of 0.77. These findings underscore the need for effective planning and strategies to manage ginger supply and enhance its production potential, thereby mitigating the risk of undersupply and market failure. Policymakers and stakeholders can utilize these forecasts to develop short- and long-term strategies for optimizing ginger production.

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Introduction

Ginger (*Zingiber officinale* L.) is an erect perennial herb, notable for its aromatic rhizomes and widespread use in culinary and medicinal applications [1, 2]. Likely originating from India, ginger has been cultivated across humid tropics, including Nigeria, since the 16th century [3]. Global production of ginger has risen significantly, from 167,025,200 kg in 2009 to 3,299,795 tonnes in 2018, with the market valued at approximately USD 2.9 billion in 2022 and projected to grow at a CAGR of 4.5% to reach USD 5-7 billion by 2028 [3-6].

As Africa's largest producer and the world's second-largest, Nigeria accounts for about 16.95% of global ginger production [7]. The country cultivates ginger on over 84,156 hectares, with notable varieties like yellow ginger (Tafin-Giwa) and black ginger (Yatsun-Biri), contributing significantly to its non-oil export revenues [7, 8]. Despite this success, Nigeria faces challenges such as price fluctuations, low yield per hectare, climatic uncertainties, and fierce competition impacting its ability to fully capitalize on its production potential [5].

The growing global demand for ginger, driven by increased health consciousness and consumer preference, highlights the

need for advanced forecasting methods to address the supply-demand gap and optimize production strategies. Supply response is fundamental to an understanding of this mechanism [9]. Supply response seeks to explain the behavior change of producers with respect to the production, consumption and exchange decisions for a certain product or a set of products arising from changes in economic incentives [10, 11].

To the best of our knowledge, no research was carried out from Nigeria on ginger supply response and with this methodology. Thus, this research aims to advance ginger supply forecasting by employing advanced time series techniques to model and forecast future ginger production while highlighting their credibility through uncertainty and probability estimates. By integrating uncertainty with these techniques, we seek to enhance forecasting accuracy, providing actionable insights for improving supply chain management and policy planning for ginger production. Additionally, incorporating maize price trends will offer a broader economic context, contributing to more effective forecasting strategies.

The main objective of this article is to study the supply response of ginger and to investigate which forecasting methods offer the best predictions with lower forecast errors and higher accuracy of forecasts.

Data and Analytical Techniques

Data for Case Studies

Time series data from 1983-2023 from Nigeria were used for the study. The data were sourced from various national and international databases that were reliable for the study. The study involves the direct use of variables and where variables cannot be found a proxy was introduced to represent the variable. All data was deemed adequate to estimate the ginger supply response. Inflation represents a range of socio-economic factors affecting farmers and decisions such as opportunity cost to save and borrow money while Relative humidity was used as a proxy variable for disease prevalence due to the correlation of humidity and disease prevalence in crops [12]. The agricultural Input index was used to represent historical data on factors used in the production of ginger. The variable and their definitions are presented in Table 1 below.

Table 1: Description of Variables

Symbol	Variable	Definition	Unit	Source
P	Ginger Production	Total Ginger Produced	kiloton	Faostat [13]
D	Disease	Disease Prevalence	Percentage	(World-Bank, [14])
IP	Input Use	Total Factors Used	-	Usda-ERS [15]
GR	Precipitation/Rainfall	Mean Annual Precipitation	Millimetre	(World-Bank, [14])
GP	Ginger Farm gate Price	Amount paid to Farmers at the farm gate	Naira per Kilogram	(Marcus, [16])
C	Domestic Consumption	National Annual Use of Ginger	Kiloton	Authors' Computation
GX	Ginger Exports	Quantity exported	Kiloton	Faostat [13]
GI	Ginger Imports	Quantity imported	Kiloton	Faostat [13]
IF	Inflation	Consumer prices Index	-	(CPI and Inflation Report - Nigeria Data Portal, [17])
MP	Maize Price	Amount paid to farmer' at the farm gate	Thousand Naira per Tonne	Authors' Computation
GY	Ginger yield	Yield realized on a Farm	Kiloton	Faostat [13]
T	Temperature on Land	Mean temperature on land	Celsius Degree	Faostat [13]
GA	Ginger Land Area	Total land area allocated to ginger cultivation	Thousand Hectare (Tha)	Faostat [13]

Source: Authors' Compilation (2024)

Analytical Techniques

Exploratory Data Analysis

To get initial insights on the data and to ensure data was suitable for analysis and forecasting. Exploratory analysis involving computation of means, minimum and maximum were employed. Skewness was evaluated for each variable to assess the symmetry of their distribution. Variables with high skewness were log-transformed to approximate normality, improving the assumptions for subsequent modelling. Additionally, multicollinearity among the predictors was tested using the Variance Inflation Factor (VIF). Predictors with VIF values exceeding the threshold of 2 were addressed to ensure model stability through removal. All values were approximated to two (2) decimal places.

Unit Root Test

The main reason to conduct a unit root test is to acquire a meaningful, valid, and non-spurious regression. For this study, the Phillips-Perron (PP) test for stationarity was used. The PP tests treat serial correlation in the test regressions by using non-parametric corrections based on estimates of the long-run variance. The main distinction between the ADF and PP tests lies in their treatment of any "nuisance" serial correlation of which the PP test tends to be more robust to a wide range of serial correlations and time-dependent heteroskedasticity [18].

The general equation and hypothesis for the PP test are as follows:
Null Hypothesis: $H_0: \gamma=0$: The series has a unit root (i.e., the

series is non-stationary)

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \varepsilon_t$$

Where: Y_t is the time series being tested; ΔY_t is the first difference of the time series ($\Delta Y_t = Y_t - Y_{t-1}$); α is a constant (drift term); βt represents a time trend (optional); Y_{t-1} is the lagged level of the time series; γ is the coefficient of interest measuring the presence of a unit root; ε_t is the error term.

Short-Run and Long-Run Supply Elasticities

The presence of cointegration is required for applying VECM to model short and long-run supply elasticities. Cointegration indicates a balance between the model's variables in the long run. Johansen's cointegration test implies the estimation of an autoregressive vector model, known as VAR, including values at levels as well as differences of non-stationary variables. At this stage, a VAR model is configured to determine the optimal lag length, and the SIC - Schwarz information criterion is applied to optimize lag lengths for the time series. The Johansen test equation is described as follows:

$$dX_t = \tau_1 dX_{t-1} + \dots + \tau_{k-1} dX_{t-k+1} + \pi X_{t-K} + \varepsilon$$

Where ε is the random variable, π and π_e demonstrate the OLS parameter matrices; πX_{t-K} examines the linear combinations of levels of X_t and the matrix π_i has the information about terms properties.

The Johansen method allows for all possible co-integrating relationships and the number of co-integrating vectors to be determined empirically. Therefore, based on trace statistics and max-eigen statistics the rejection of the null hypothesis is necessary with a significance level of 5% for the confirmation of long-term cointegration between the model variables.

Second, suppose the null for no co-integration is rejected. In that case, the lagged residual from the co-integrating regression is imposed as the error correction term in a vector error correction model (VECM). A VECM model for the study is shown below: $\Delta P_t = \Gamma_1 \Delta P_{t-1} + \Gamma_2 \Delta T_{t-1} + \Gamma_3 \Delta G_{t-1} + \Gamma_4 \Delta GR_{t-1} + \Gamma_5 \Delta D_{t-1} + \Gamma_6 \Delta GX_{t-1} + \Gamma_7 \Delta GI_{t-1} + \Gamma_8 \Delta IF_{t-1} + \Gamma_9 \Delta IP_{t-1} + \Gamma_{10} \Delta MP_{t-1} + \alpha_1(\beta_1 P_{t-1} + \beta_2 T_{t-1} + \beta_3 G_{t-1} + \beta_4 GR_{t-1} + \beta_5 D_{t-1} + \beta_6 GX_{t-1} + \beta_7 GI_{t-1} + \beta_8 IF_{t-1} + \beta_9 IP_{t-1} + \beta_{10} MP_{t-1}) + \epsilon_t$

Where: The first part involving Γ captures the short-run adjustments or the short-run supply elasticities in the first differences of the variables; $\beta_1, \beta_2, \dots, \beta_{10}$ are the long-run coefficients in the cointegrating vector, describing the equilibrium relationship and these represent the long-run supply elasticities; α is the speed of adjustment, indicating how fast the system corrects any deviation from the long-run equilibrium; ϵ_t is the stochastic error term assumed to be independently and normally distributed with zero mean and constant variance.

Forecasting Techniques

ETS Model

The state-space model of the ETS method allows for a flexible treatment of error, trend, and seasonal components, adapting the weights dynamically based on the underlying data patterns. The forecast was made considering a weighted average of past observations where the succeeding observations are exponentially given more weight than earlier preceding ones [19]. The possibilities for each component are Error = (A, M), Trend = (N, A, Ad), and Seasonal = (N, A, M). The letters A, M, N, and Ad refer to additive, multiplicative, none, and additive damped, respectively [20]. For instance, the ETS (A, A, M) was the method with the additive trend, multiplicative seasonality, and additive errors [21, 23]. By using the state-space structure, the optimal exponential smoothing model could be determined. According to the model-building algorithm from the “forecast” package, the ets function was utilized to determine the final ETS model, defined as the model with the lowest AICc value among models developed from 30 iterative choices [23-25].

ARIMA Model

ARIMA is a generalized model of Autoregressive Moving Average (ARMA) that combines Autoregressive (AR) process and Moving Average (MA) processes and builds a composite model of the time series [26]. While the AR uses the dependencies between an observation and several lagged observations. The I, integrated by measuring the differences in observations at different times

makes the series stationary. The Moving Average considers the dependency between observations and the residual error terms when a moving average model is used for the lagged observations.

The forecasting equation for this study is given by:

$$\hat{y}_{t+h} = \delta + \phi_1 \hat{y}_{t+h-1} + \phi_2 \hat{y}_{t+h-2} + \dots + \phi_p \hat{y}_{t+h-p} + \theta_1 \epsilon_{t+h-1} + \theta_2 \epsilon_{t+h-2} + \dots + \theta_q \epsilon_{t+h-q}$$

Where: y_t is the value of the time series at time t ; δ is the drift term; $\phi_1, \phi_2, \dots, \phi_p$ are coefficients for the AR terms; $\theta_1, \theta_2, \dots, \theta_q$ are coefficients for MA terms; ϵ_t is the white noise at each time t ; p is the number of AR terms (autoregressive order); q is the number of MA terms (moving average order); d is the number of differences or integrated order, I ; $\hat{y}_{t+h}$ is the forecast for h steps ahead.

Prophet Model

Prophet is an open-source time-series forecasting library developed by Facebook composed of three key components. The first component is called trend and is used to describe the trend in the time series data. The second component is seasonality and the third component is holidays.

According to the forecasting equation for the model is given by [27]:

$$\hat{y}(t+h) = g(t+h) + s(t+h) + h(t+h)$$

Where $\hat{y}(t+h)$ is composed of predicted trend $g(t+h)$, seasonal $s(t+h)$ and holiday effect.

Uncertainty and Model Performance

Monte Carlo simulations and error metrics were employed to evaluate both the uncertainty and accuracy of the forecast models. Monte Carlo Simulation is a mathematical technique used to estimate potential outcomes of uncertain events by simulating random sampling from a probability distribution [28]. This approach allows for exploring a wide range of possible future results by generating multiple iterations of the forecast using random inputs.

For this study, the Monte Carlo simulation was repeated 1,000 times, producing many possible outcomes for each model. Each iteration is randomly sampled from the range of values between the minimum and maximum uncertainty bounds. From these simulations, the mean, 2.5%, and 97.5% percentiles of the 95% confidence interval were computed. These results were then compared with the point forecasts of each model to better understand the uncertainty surrounding the predictions.

To measure the accuracy of the models, various error metrics were calculated, including: (i) Root Mean Squared Error (RMSE): to measure the average magnitude of the errors; (ii) Mean Absolute Percentage Error (MAPE): to assess the percentage error between forecasted and actual values; (iii) Mean Absolute Scaled Error (MASE): to evaluate the accuracy of the forecast relative to a naive model.

Results and Discussion

Table 2: Exploratory Data Analysis

Variables	Minimum	Maximum	Mean	Skewness	VIF score	PP-test (Level) Inference
P	3	834.63	232.37	1.246	-	Accept H0
GY	5	94.09	27.74	0.979	7.100	Accept H0
T	-0.36	1.53	0.8168	-0.579	1.353	Accept H0
GP	33.82	68.71	53.3724	0.162	1.429	Accept H0
GR	888.06	1296.78	1164.4146	-0.938	1.333	Accept H0
D	55.07	57.56	56.56	-0.446	1.640	Accept H0
GX	0.534	37.36	10.17	1.263	1.659	Accept H0
GI	0	2	0.34	2.52	1.306	Accept H0
IF	-3.73	72.84	18.38	1.416	1.812	Accept H0
GA	6	191	100.12	0.006	6.695	Accept H0
IP	34	116	73.1366	0.206	1.596	Accept H0
MP	3.32	513.61	69.25	2.766	1.273	Accept H0
C	2.09	805.05	222.46	1.251	5.905	Accept H0

Source: Authors' computation (2024) using SPSS software V.26

The result of the exploratory analysis indicates that all the variables were moderately collinear except Ginger yield, area, and domestic consumption as such they were discarded due to their VIF scores above the threshold [29]. Also, the preliminary investigation of the PP test resulted in all the variables being non-stationary which warrants further differencing to achieve stationarity. All variables were also skewed in different directions thus, log normalization was used to transform them to help achieve stability and normality.

Table 3: Unit Root Test at First Difference

Variables	Z(Alpha)	P-values	Truncation lag parameter	Significance level	Conclusion
P	-41.50	0.01	3	5%	Reject H0
T	-42.97	0.01	3	5%	Reject H0
D	-42.78	0.01	3	5%	Reject H0
GR	-55.59	0.01	3	5%	Reject H0
IF	-38.55	0.01	3	5%	Reject H0
GP	-37.07	0.01	3	5%	Reject H0
MP	-48.64	0.01	3	5%	Reject H0
IP	-50.88	0.01	3	5%	Reject H0
GI	-42.80	0.01	3	5%	Reject H0
GX	-29.65	0.01	3	5%	Reject H0

Source: Authors' computation (2024) using urca package on R version 4.4.0 (2024-04-24 ucrt)

The above result of PP test indicates that all variables become stationary after transformation and differencing at 5% significance level. According to the PP test, the Null hypothesis that the series has a unit root and considered non-stationary will be rejected since all the p-value were lower than the 5% significance level [30].

Table 4: Johansen Test for Long-Run Relationship

Series: P, T, D, GR, IF, GP, MP, IP, GI, GX

Test type (CE)	Trace result	Critical Value (10%)	Critical Value (5%)	Critical Value (1%)	Eigenvalue (Lambda)	Conclusion
$r \leq 7$	28.84	28.71	31.52	37.22	3.44e-01	Reject H0 at 10%
$r \leq 6$	55.51	45.23	48.28	55.43	5.04e-01	Reject H0
$r \leq 5$	86.78	66.49	70.60	78.87	5.61e-01	Reject H0
$r \leq 4$	133.47	85.18	90.39	104.20	7.07e-01	Reject H0
$r \leq 3$	192.05	118.99	124.25	136.06	7.86e-01	Reject H0
$r \leq 2$	264.38	151.38	157.11	168.92	8.51e-01	Reject H0

$r \leq 1$	344.78	186.54	192.84	204.79	8.79e-01	Reject H0
$r = 0$	449.95	226.34	232.49	246.27	9.37e-01	Reject H0

Source: Authors' computation (2024) using urca package on R version 4.4.0 (2024-04-24 ucrt)

The result of the Johansen cointegration shows several cointegrating relations between the variables. About seven cointegrating relationships were found which suggests a strong presence of cointegration. According to the literature therefore we can continue with the VECM.

Table 5: Vector Error Correction Model Analysis

Long-run			
Variable	Coefficient	Standard Error	Test Statistic
Pt	1*	0.09	11.32
IPt	15.74*	0.09	-58.51
GXt	-0.45*	0.11	10.37
GPt	-3.24*	0.08	-15.67
Dt	-93.96*	0.09	5776.28
GIIt	0.33*	0.11	-20.54
IFt	0.07*	0.08	-19.80
MPt	1.78*	0.08	-82.42
Tt	-2.02*	0.08	273.42
GRt	-15.31*	0.11	-16.70
Constant	-0.57	-	-
Short-run			
Variable	Coefficient	Standard Error	Test Statistic
Pt-1	-0.64***	0.34	-1.87
IPt-1	-0.06**	0.75	-2.01
GXt-1	-0.55	2.18	-0.99
GPt-1	0.08	0.23	1.40
Dt-1	-0.01	2.33	-1.04
GIIt-1	-0.04	19.85	-0.03
IFt-1	0.67*	0.059	0.73
MPt-1	-0.14	0.07	-0.40
Tt-1	0.14	0.26	2.62
GRt-1	-0.04	1.86	-0.49

Source: Authors' computation (2024) using tsDyn, dplyr, and Metrics packages on R version 4.4.0 (2024-04-24 ucrt)

*Significant at 1%, ** Significant at 5%, *** Significant at 10%

F-stat = 2.803** $R^2 = 0.486$ Adjusted $R^2 = 0.314$ RMSE = 0.399 MAPE = 3.27% MAE = 0.291

Ljung-box p-value = 0.0984 (No significant autocorrelation in residuals)

Breusch Pagan test = 0.996 B = 5.1648 (No evidence of heteroskedasticity)

The results of the VECM show that all variables were significant in the long run with disease prevalence and input use having the largest coefficients of -93.96 and -15.74. The negative sign indicates that these variables responded negatively to ginger production as affirmed by that in 2023 alone Nigerian farmers lost over 2 billion due to ginger disease [31]. In the short run, only input use and inflation were affecting ginger production highlighting the importance of these variables as having direct and short-term immediate effects on ginger production. This is affirmed by the economic theory that two-digit inflation reduces the purchasing power of the consumer and this serves as a disincentive to production. The tests for autocorrelation and heteroscedasticity also indicate that they were not an issue in the analysis. The R^2 of 48.6% and 31.4% also show significant fit. The RMSE and MAPE values of 0.399 and 3.27% also indicate that the model performs well and captures the variances in the data.

Table 6: ETS Model (AAN) with Monte-Carlo Simulation in Kiloton

Year	Point Forecast	MC Mean	MC 2.5% Percentile	MC 97.5% Percentile
2024	464.76	467.29	192.23	733.36
2025	476.19	475.81	192.35	782.79
2026	487.62	489.34	138.73	835.75
2027	499.05	501.62	130.98	864.27
2028	510.48	505.01	106.89	884.58
2029	521.91	516.94	71.43	937.49
2030	533.34	536.55	60.55	1005.97
2031	544.77	540.53	71.50	1030.77
2032	556.21	557.44	76.58	1088.64
2033	567.64	564.64	40.08	1101.33

Source: Authors' computation (2024) using packages ets, forecast, MonteCarlo, dplyr on R version 4.4.0
AIC = 1122.18 BIC = 1127.319 AICc = 1122.827 Alpha = 0.568171 Beta = 0.000123 Gamma = 0.087078 RMSE = 127407

Table 7: Prophet Model with Monte-Carlo Simulation in Kiloton

Year	Point Forecast	MC Mean	MC 2.5% Percentile	MC 97.5% Percentile
2024	612.12	605.66	332.84	866.29
2025	644.80	638.16	402.60	910.77
2026	594.32	628.21	343.62	869.99
2027	607.75	668.33	422.22	927.21
2028	689.59	694.65	401.41	981.99
2029	721.53	713.35	480.59	965.39
2030	668.82	735.83	384.12	1085.52
2031	671.69	709.67	455.27	949.22
2032	757.81	726.12	520.24	985.72
2033	788.62	768.59	477.16	1051.49

Source: Authors' computation (2024) using packages predict(), forecast(), prophet(), MonteCarlo, dplyr on R version 4.4.0
AIC = 3.696 BIC = 3.696 Log-likelihood = -1.84778

Table 8: Arima (0,1,0) Model with Monte-Carlo Simulation in Kiloton

Year	Point Forecast	MC Mean	MC 2.5% Percentile	MC 97.5% Percentile
2024	259.51	270.03	117.60	510.89
2025	289.33	327.29	98.49	824.09
2026	322.58	407.79	90.25	1260.36
2027	359.66	490.93	83.06	1645.46
2028	400.99	581.82	72.11	2064.16
2029	447.07	703.94	66.58	2809.14
2030	498.45	837.65	60.29	3706.42
2031	555.73	998.68	59.69	4448.56
2032	619.59	1187.62	61.38	5687.14
2033	690.80	1440.36	61.92	6641.94

Source: Authors' computation (2024) using packages forecast(), auto.arima(), MonteCarlo, dplyr on R version 4.4.0
AIC = 40.3605 BIC = 43.7383 AICc = 40.68 RMSE = 465125.3 Sigma² = 0.149 Log-likelihood = -18.18 Drift coefficient = 0.1088 (s.e. 0.0603)

The result of the forecast above shows relatively different forecasts for the three models (ETS, ARIMA, and Facebook PROPHET model). The point forecast indicates the model's best line of forecast from the series provided. The Monte Carlo simulations indicated the uncertainty and probability of occurrence of various possible productions over the 10-year forecast horizon. ARIMA and ETS orders were automatically obtained from various iterations during the analysis as the model with the least AICc [23]. The result of the forecast indicates high uncertainty as the year goes by signalling unstable production for the time horizon.

Table 9: Performance Measurement

Metric	ETS (AAN)	ARIMA (0,1,0)	PROPHET
Mean Absolute Scaled Error (MASE)	0.96	0.77	1.44
Mean Absolute Percentage Error (MAPE)	36.53%	1.34%	3.24%
R ²	0.7477	0.96	0.90

Source: Authors' computation (2024) using packages Metrics on R version 4.4.0 (2024-04-24 ucr)

The model performance indicates that ARIMA (0,1,0) with MASE of 0.77 and ETS with 0.96. This means that the models perform significantly well and better than the naïve forecast. However, the MASE of the PROPHET model was found to be 1.44 which means that the model performs worse than the naïve forecast, and thus results are highly unreliable. ARIMA model has a significantly lower MAPE of 1.34% than the ETS model which signifies that the model captures the variance during the forecast well. Also, result of R² revealed that the data was reliable to all the models with 96%, 74.77%, and 90%; however, ETS and ARIMA better capture the dynamics in the data with less error. The ETS (ANN) indicates that the best-performing model possesses Additive error, No trend, and No seasonality.

Conclusion

The analysis shows that the variables used were fit for the supply response and forecast as shown by cointegration analysis. In the long run elasticities, all the variables were highly significant with disease prevalence showing the greatest impact. The forecast result indicated the need for employing multiple models to forecast ginger production and indicated high uncertainty and probabilistic in ginger production. Also, the ARIMA (0,1,0) and ETS models were the best-performing models for ginger supply from Nigeria.

References

1. Aleem M, Khan MI, Shakshaz FA, Akbari N, Anwar D (2020) Botany, phytochemistry, and antimicrobial activity of ginger (*Zingiber officinale*): A review. *International Journal of Herbal Medicine* 8: 36-41.
2. Singh P, Srivastava S, Singh VB, Sharma P, Singh D (2018) Ginger (*Zingiber officinale*): A novel herbal remedy. *International Journal of Current Microbiology and Applied Sciences* 7: 4065-4077.
3. Bamigboye T (2023) Food, fiber, fuel - Ginger production in the tropics: A paradigm shift for non-oil export. *Foodlog* <https://agrifoodnetworks.org/article/ginger-production-in-the-tropics-a-paradigm-shift-for-non-oil-export>.
4. MOAD (2018). Annual statistical information on Nepalese agriculture. Ministry of Agricultural Development. Government of Nepal <https://moald.gov.np/content/42/statistical-information-on-nepalese-agriculture/>.
5. FAOSTAT (2020) Faostat database. Rome, Italy: Food and Agriculture Organization of the United Nations <https://www.fao.org/home/en>.
6. Abhishek A (2023) Top 10 ginger-producing countries & states in India - Agriculture review. *Agriculture Review* <https://agriculturereview.com/top-10-ginger-producing-countries-and-states-in-india>.
7. Global Ginger Market Report and Forecast 2024-2032 (2024) Expert Market Research. <https://www.expertmarketresearch.com/reports/ginger-market>.
8. Centre for the Promotion of Imports from Developing Countries (CBI) Nigerian Export Promotion Council (NEPC), et al. (2023). NEPC/CBI Nigeria sustainable ginger programme: Market orientation mission to Netherlands and France <https://nepc.gov.ng/cms/wp-content/uploads/2023/05/CBI-Presentation.pdf>.
9. Tanko M, Iddrisu A, Alidu AF (2016) Determinants of rice yield in the Northern region of Ghana: The role of policy. *Asian Journal of Agricultural Extension Economics & Sociology* 9: 1-11.
10. Nerlove M, Bachman KL (1960) The analysis of changes in agricultural supply: Problems and approaches. *Journal of Farm Economics* 42: 531-554.
11. Ajetomobi JO (2010) Supply response, risk, and institutional change in Nigerian agriculture. *African Economic Research Consortium Research Paper* 197: 1-56.
12. Pokhrel B (2021) Effects of environmental factors on crop diseases. *Journal of Plant Pathology & Microbiology* 12: 553.
13. FAOSTAT (2024) <https://www.fao.org/faostat/en/#data/Nigeria>.
14. World Bank (2021) Climate data projections: Nigeria. Climate Change Knowledge Portal. <https://climateknowledgeportal.worldbank.org/country/nigeria/climate-data-projections-general>.
15. US Department of Agriculture, Economic Research Service (2023) International agricultural productivity. <https://www.ers.usda.gov/data-products/international-agricultural-productivity/>.
16. Marcus PL (2019) Analysis of supply response and trend of ginger production in Benue and Kaduna States, Nigeria (PhD dissertation). FUTMINNA Institutional Repository.
17. CPI and Inflation Report - Nigeria Data Portal (2024) Knoema <https://nigeria.opendataforafrica.org/NGNBSNCP1R2017/cpi-and-inflation-report>.
18. Syriopoulos T (2004) International portfolio diversification to Central European stock markets. *Applied Financial Economics* 14: 1253-1268.
19. Hidayatullah H, Parasian S (2020) Comparison of forecasting accuracy rate of exponential smoothing method on admission of new students. *Journal of Critical Reviews* 7: 268-274.
20. Hyndman RJ, Koehler AB, Ord JK, Snyder RD (2008) Forecasting with exponential smoothing: The state space approach. Berlin: Springer <https://doi.org/10.1007/978-3-540-71918-2>.
21. Heydari M, Ghadim HB, Rashidi M, Noori M (2019) Application of Holt-Winters time series models for predicting climatic parameters: A case study from Robat Garah-Bil Station, Iran. *Polish Journal of Environmental Studies* 29: 617-627.
22. Hyndman RJ, Athanasopoulos G (2018) Forecasting: Principles and practice (2nd ed.) Melbourne, VIC: OTexts <https://otexts.com/fpp2>.
23. Wang Y, Xu C, Ren J, Zhao X, Chao L, et al. (2020) Secular seasonality and trend forecasting of tuberculosis incidence rate in China using the advanced error-trend-seasonal framework. *Infection and Drug Resistance* 13: 733-747.
24. Punyapornwithaya V, Jampachaisri K, Klaharn K, Sansamur

- C (2021) Forecasting of milk production in Northern Thailand using seasonal ARIMA, error trend seasonality, and hybrid models. *Frontiers in Veterinary Science* 8: 775114.
25. Ke G, Hu Y, Huang X, Peng X, Lei M, et al. (2016) Epidemiological analysis of hemorrhagic fever with renal syndrome in China with the seasonal-trend decomposition method and the exponential smoothing model. *Scientific Reports* 6: 39350.
26. Fattah J, Ezzine L, Aman Z, Moussami HE, Lachhab A (2018) Forecasting of demand using ARIMA model. *International Journal of Engineering Business Management* 10: 184797901880867.
27. Oo ZZ, Phyu S (2020) Time series prediction based on Facebook Prophet: A case study, Temperature forecasting in Myintkyina. *International Journal of Applied Mathematics Electronics and Computers* 8: 263-267.
28. Luengo D, Martino L, Bugallo M, Elvira V, Särkkä S (2020) A survey of Monte Carlo methods for parameter estimation. *EURASIP Journal on Advances in Signal Processing* 1: 2-62.
29. Johnston R, Jones K, Manley D (2018) Confounding and collinearity in regression analysis: A cautionary tale and an alternative procedure. *Quality & Quantity* 52: 1957-1976.
30. Phillips PCB, Perron P (1988) Testing for a unit root in time series regression. *Biometrika* 75: 335-346.
31. Egboboh C (2024) Nigerian farmers lose over ₦12bn to ginger blight outbreak - FG. *Businessday NG* <https://businessday.ng/news/article/nigerian-farmers-lose-over-12bn-to-ginger-blight-outbreak-fg/>.