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Building a Suitable GARCH Model for Accuracy Measurement of Selected Components of the Somalia Agro-Economy

Ahmed, Z.A., *Nkpordee, L., & Belwade, A.A.A.
Department of Mathematics and Statistics, Kampala International University, Kampala, Uganda

***Corresponding author email:** lekia.nkpordee@kiu.ac.ug

Abstract
This study investigates the volatility patterns in Somalia's agro-economy by applying GARCH models to key economic indicators, including GDP rate, livestock production index, and crop production index. Using time series data, the study assesses stationarity, estimates model parameters, and compares various GARCH specifications based on information criteria to identify the most suitable model for forecasting economic trends. The findings reveal significant fluctuations in agricultural productivity and GDP, with the APARCH (2,1) model emerging as the best fit for capturing volatility. The forecast results indicate periods of economic uncertainty, highlighting potential external shocks such as climate change and geopolitical instability. This study provides critical insights for policymakers, emphasizing the need for strategic interventions to enhance economic resilience and sustainable agricultural development in Somalia. A key recommendation is for the Somali government to implement robust risk management strategies, such as climate adaptation policies and financial support systems, to mitigate the adverse effects of agro-economic volatility.

Keywords: Volatility Forecasting, GARCH Modeling, Agro-Economic Stability, Risk Management, Price Fluctuations

Introduction

In the realm of agricultural economics, accurately forecasting price volatility is paramount for stakeholders ranging from policymakers to individual farmers. The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model has emerged as a pivotal tool in this endeavor, offering nuanced insights into market dynamics. For instance, a study employing the GJR-GARCH-MIDAS model highlighted the significant impact of geopolitical risks on international agricultural markets, underscoring the model's robustness in capturing complex volatility patterns (Dai et al., 2024). Similarly, in their research on the Nigerian economy, Nkpordee and Ogolo (2022) demonstrated the effectiveness of GARCH models in measuring economic fluctuations, further validating the model's relevance in economic forecasting. Region-specific applications of GARCH models further demonstrate their versatility. In Ethiopia, researchers applied GARCH, TGARCH, and EGARCH models to analyze price volatility of commodities like Teff and Red Pepper, revealing the presence of leverage effects where negative news had a more pronounced impact on volatility than positive news (Dinku, 2021). Likewise, in Nigeria, the GARCH(1,1) model was identified as the best fit for assessing the influence of savings accumulation on the economy, highlighting its efficacy in economic forecasting (Nkpordee & Ogolo, 2022). These studies emphasize the model's adaptability in different economic settings.

The East African region, with its diverse agricultural landscape, presents unique challenges and opportunities for such modeling techniques. A study on the co-movement among different agricultural commodity markets using a copula-GARCH approach emphasized the interconnectedness of these markets and the necessity for tailored models to capture regional specificities (Zhang & Chen, 2020). In Ethiopia, the application of GARCH family models to agricultural commodities like Teff, Wheat, Barley, and Maize demonstrated the models' effectiveness in forecasting price volatility, providing valuable insights for risk management (Dessie et al., 2023). These findings suggest the need for a similar study in Somalia to assess the suitability of GARCH models for economic forecasting in its agro-economy. Building upon these regional studies, the application of GARCH models to Somalia's agro-economy holds promise. The country's agricultural sector is highly susceptible to market uncertainties caused by climate variability, trade policies, and economic instability. A robust GARCH model tailored to Somalia's agricultural economy can provide stakeholders with reliable forecasts of price fluctuations, enabling informed decision-making for economic stability and growth.

Somalia's agro-economy is characterized by significant price volatility due to unpredictable climatic conditions, political instability, and fluctuating market demands. The lack of a reliable forecasting model makes it challenging for policymakers and farmers to mitigate economic risks effectively. This study aims to build a suitable GARCH model to measure accuracy in predicting the volatility of selected agricultural components in Somalia. By assessing various GARCH model specifications, including asymmetric models such as TGARCH and EGARCH, this research seeks to determine the best-fit model for capturing the unique market behaviors of Somalia's agro-economy. The findings will provide a scientific basis for better economic planning, risk management, and policy formulation in the agricultural sector.

The specific objectives for this study are to:

i. To analyze the series plots and identify the year with the highest values for livestock production index, crop production index, and GDP rate in Somalia.
ii. To assess the normality and test for stationarity of the datasets under study to ensure their suitability for modeling.
iii. To estimate the parameters of various GARCH models and evaluate their performance in capturing volatility in Somalia's agro-economy.
iv. To compare and select the most appropriate GARCH model for forecasting based on model selection criteria such as AIC, BIC, and log-likelihood values.

Materials and Methods

Data Source and Type

A secondary time series data was used in this investigation. The statistical database websites of the World Bank and United Nation Statistics Division (UNSD) such as (https://data.worldbank.org and https://unstats.un.org/UNSDWebsite/) were used to access data for this study. The data was collected annually from period of 1990 to 2023 based on the selected agricultural production indexes and GDP growth under study. The GRETL (32c) statistical software was utilized for data analysis.

Model Specification

GARCH (p, q) Model

The GARCH model specifically the GARCH (p, q) model, extends the ARCH (Autoregressive Conditional Heteroskedasticity) model by allowing the conditional variance to depend on both past squared innovations and past variances.

The mean equation is given as:

$$r_t = \mu + \epsilon_t \quad (1)$$

where:

r_t: is the return at the time.

μ: is the mean return.

ϵ_t: is the error at time t, which is assumed to be normally distributed with mean zero and conditional variance σ_t^2.

The variance equation is represented by:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \epsilon_t^2 + \sum_{j=1}^{p} \beta_j \alpha_{t-j}^2 \quad (2)$$

where:

α_t^2 is the conditional variance at time t.

α_0 is a constant term (must be positive)

α_i are the coefficients for the lagged squared residuals (i.e., past squared errors) ϵ_t^2 must be non- negative.

β_j are the coefficients for the lagged conditional variance α_{t-j}^2 (must be non-negative).

Moreover, the following GARCH model offers a different approach to capturing the volatility dynamics in time series:

GARCH (1, 1) Model

The conditional mean equation is given as:

$$y_t = \mu + \epsilon_t \quad (3)$$

Whereas the conditional variance equation is represented by:

$$\sigma_i^2 = \overline{\omega} + \alpha_i \varepsilon_{i-1}^2 + \beta_1 \sigma_{i-1}^2 + \lambda_1 X_i^2 \quad (4)$$

GARCH (1, 0) Model

The conditional variance equation in (4) is reduced to equation (5) below GARCH (1, 0) Model

$$\sigma_i^2 = \overline{\omega}_i + \beta_1 \sigma_{i-1}^2 + \lambda_1 X_i^2 \quad (5)$$

GARCH (0, 1) model

The conditional variance equation in (4) is also reduced to equation (6) below GARCH (0, 1) model

$$\sigma_i^2 = \overline{\omega} + \alpha_i \varepsilon_{i-1}^2 + \lambda_1 X_i^2 \qquad (6)$$

where:
ω is constant term in the variance aquation.
λ_1 is the coefficient of dependent variable.
X_i^2 is the independent variable and $\overline{\omega}$ is the constant coefficient.

EGARCH (1,1) Model

The conditional variance equation for an EGARCH (1,1) model is given by

$$\log(\sigma_t^2) = \omega + \sigma_t \frac{\epsilon_{t-1}}{\sigma_{t-1}} + \beta_1 \log(\sigma_{t-1}^2) \qquad (7)$$

where
$\log(\sigma_t^2)$ is the log of the conditional variance.
Ω is the constant term.
α_1 is the coefficient for the standardized residuals.
β_1 is the coefficient for the log of lagged conditional variance.

Integrated GARCH Model

The conditional variance equation for an integrated GARCH model is denoted by

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \alpha_{t-j}^2 \qquad (8)$$

where
σ_t^2 is the conditional variance at time t.
Ω is the constant term.
α_i are the coefficients for lagged squared residuals.
β_j are the coefficients for lagged conditional variances.

Diagnostic Tests

Normality Test

A test statistic known as Jarque-Bera is used to determine if a series is normally distributed. The test statistic computes the deviation of the series' skewness and kurtosis from the normal distribution. It is computed as:

$$JB = \frac{N}{6} [S^2 + \frac{(K-3)^2}{4}] \qquad (9)$$

where:
N= Number of years or observation
S^2 = Skewness
K = Kurtosis

Stationarity

Stationarity refers to a property of a time series where its statistical properties, such as mean, variance and autocorrelation are constant over time. A stationary time series has a consistent and predictable structure, making it easier to model and forecast. And its hypothesis is given by:
$H_0 : X_t$ is non – stationary;
$H_1 : X_t$ is stationary.

For checking stationarity, we employ the Augmented Dickey Fuller (ADF) method to determine whether a unit root exist in the time series of the data utilized in this investigation. The regression equations of the ADF test are defined as:

$$\Delta V_t = \eta V_{t-1} + \eta \sum_{i=1}^{N} \Delta V_{t-j} + \epsilon_i \qquad (10)$$

$$\Delta V_t = \alpha_0 + \lambda V_{t-1} + \eta \sum_{i=1}^{N} \Delta V_{t-j} + \epsilon_i \qquad (11)$$

$$\Delta V_t = \alpha_0 + \lambda_{1i} V_{t-1} + \eta \sum_{i=1}^{N} \Delta V_{t-j} + \epsilon_i \qquad (12)$$

where:
ΔV_t: is the change in the variable V at time t.
V_{t-1}: is the value of the variable V at the previous time period t−1.
α_0: is a constant term, often representing the intercept in the equation.
λ: is a parameter representing the lagged effect of V_{t-1} on V_t.
ϵ_i: is the error term or residual, capturing the random noise or unexplained variation in the model.

λ_{1i}: is a specific parameter for the lagged variable V_{t-1}, possibly indicating a different effect for different entities i.

Tests for Heteroskedasticity

According to Mirer (1995) Heteroskedasticity is the situation in which the standard deviations of the errors are not the same for all the observations. The Lagrange Multiplier (LM) test will be used to determine heteroskedasticity. As a result, testing for heteroskedasticity is essentially testing for the ARCH effect. A null hypothesis of no ARCH effect must be stated, and if the test is significant, we shall proceed with estimate using GARCH models. The Lagrange Multiplier test use OLS to identify the most appropriate regression equation. The purpose of linear regression model is to compute the residuals.

Log-Likelihood

In the log-likelihood function for the GARCH (1,1) is given by:

$$L(\theta) = -\frac{T}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\left[\log(\sigma_t^2) + \frac{\epsilon_t^2}{\sigma_t^2}\right] \quad (13)$$

The parameters and terms are defined as follows:

L(θ): is the log-likelihood function for the GARCH (1,1) model. It measures how well the model parameters θ explain the observed data.

T: is the number of observations in the time series data. It represents the total count of data points used in the estimation.

θ: is the vector of parameters to be estimated.

$\frac{\epsilon_t^2}{\sigma_t^2}$: is the standardized squared residual. It measures how far the actual residual $\in_t$ is from its conditional variance σ_t^2.

$\log(\sigma_t^2)$: is the natural logarithm of the conditional variance. This term penalizes large conditional variances and ensures the variance is always positive.

Model Selection Criteria

Akaike Information Criteria (AIC)

The AIC evaluates a statistical model's relative goodness of fit. The AIC value is given by

$$\text{AIC} = \text{T} \times ln\left(\frac{e^2}{T}\right) + 2 \times p \quad (14)$$

where:

T is the quantity of observations (data points);

ln is the natural logarithm;

e^2 is the residual sum of squares.

p stands for the model's parameter count.

Bayesian Information Criteria (BIC)

The BIC is a model selection criterion that involves selections among a finite set of models. The BIC is given by:

$$\text{BIC} = \text{T} \times ln\left(\frac{e^2}{T}\right) + p \times ln(\text{T}) \quad (15)$$

Hannan- Quinn Criteria (HQC)

The HQC is a model selection criterion that involves selections among a finite set of models. The HQC is given by

$$\text{HQC} = \text{T} \times ln\left(\frac{e^2}{T}\right) + p \times ln[ln(\text{T})] \quad (16)$$

Model Accuracy Measurement

Mean Absolute Error (MAE)

One commonly used metric for evaluating the accuracy of financial models like GARCH is the Mean Absolute Error (MAE), which measures the average magnitude of errors between the model's predictions and the actual observed values. The MAE is given by:

$$\text{MAE} = \frac{1}{\text{n}}\sum_{\text{i}}^{\text{n}} |\,\text{y}_\text{i} - \hat{\text{y}}_\text{i}\,| \quad (17)$$

where:

n: is the number of observations.

y_i: is the actual value for the i-th observations.

$\hat{\text{y}}_\text{i}$: is the predicted value for the i-th observation.

Mean Square Error (MSE)

MSE is the average squared differences between the predicted and actual values. This metric is useful for highlighting models that have large errors but can be sensitive to outliers. And it's given by:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i}^{n} (y_i - \hat{y}_i)^2 \tag{18}$$

Root Mean Square Error (RMSE)

The Root Mean Squared Error (RMSE) provides a comprehensive measure of the model's predictive performance by accounting for both bias and variance in the prediction errors. The RMSE is computed as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\left(\sum_{i}^{n} (y_i - \hat{y}_i)^2\right)} \tag{19}$$

Results

Data Visualization

Figure 1 below shows the GDP growth rates over time, from around 1990 to 2021. As illustrated, there are significant fluctuantions in the GDP growth rates throughout the years. In 1994, there is notable dip, where the GDP rate falls to approximately -20%, indicating a major economic contraction. In 1996, the GDP rates rise sharply, entering positive territory and stabilizing between 0% and 10% for a prolonged period. A significant spike is observed around 2015, where GDP rates surge to nearly 25%, followed by an equally sharp decline. After this peak, flactuations continue, but rates remain relatively close to zero, with small positive and negative variations, indicating a more stable yet less dynamic economic growth. Overall, the figure 4.1 highlights periods of economic instability with sharp peaks and trouphs, particularly around the early 1990s and mid-2010s. Figure 2 below presents the Livestock production Index (LVI) plot. showing trends from 1990 to 2023. Initially, there is a sharp decline in the index from 1990, reaching its lowest point in 1992. After this dip, the index demonstrates a steady increase, peaking in the early 2000s, indicating a recovery and subsequent growth in livestock production. The period from around 2005 to 2010 exhibits some volatility, with a noticeable peak in 2013. After this peak, there are fluctuations, but the general trend appears to be slightly declining, particularly after 2015, when the index begins to stabilize at a lower level compared to its peak. This pattern suggests challenges in sustaining higher production levels, possibly due to environmental factors, market conditions or changes in agricultural practices.

Figure 3 below shows the Crop Production Index (CPI) patterns over time. It starts at a high point in 1990, followed by a sharp decline, similar to livestock Production Index (LPI). The lowest pint is reached in 1992, after which there is a gradual recovery. Unlike the LPI, the CIP does not show a consistent upward trend but rather shows more pronounced fluctuations. Following a partial recovery in 1994, the index experiences cycles of increases and decreases, with peaks around 2005 and 2010. However, the index remains relatively unstable, with no clear long-term growth trend, slightly declining toward the latter years of the series. This suggests that CPI might be more susceptible to external factors such as climate change, pest outbreaks and farming techniques.

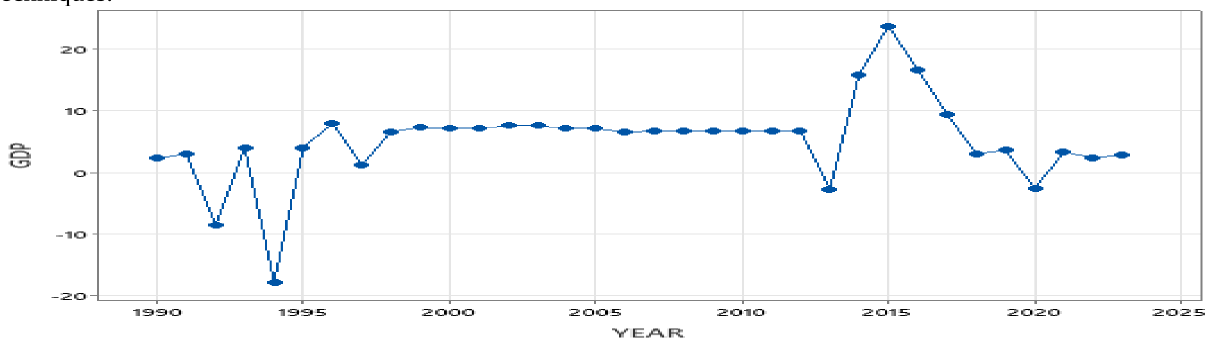

Figure 1: Time Series Plot for GDP Rate of Somalia

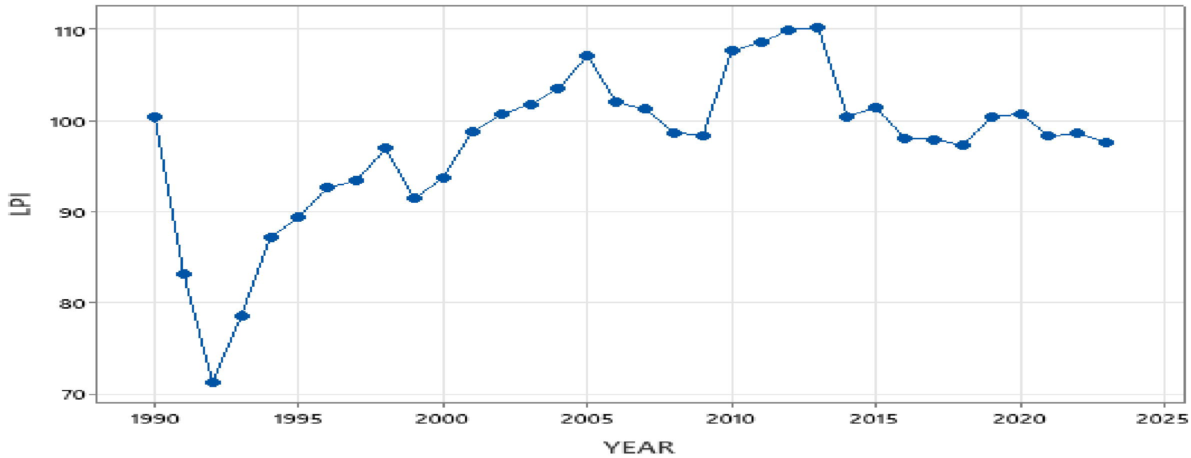

Figure 2 Time Series Plot for Livestock Production Index (LPI) of Somalia

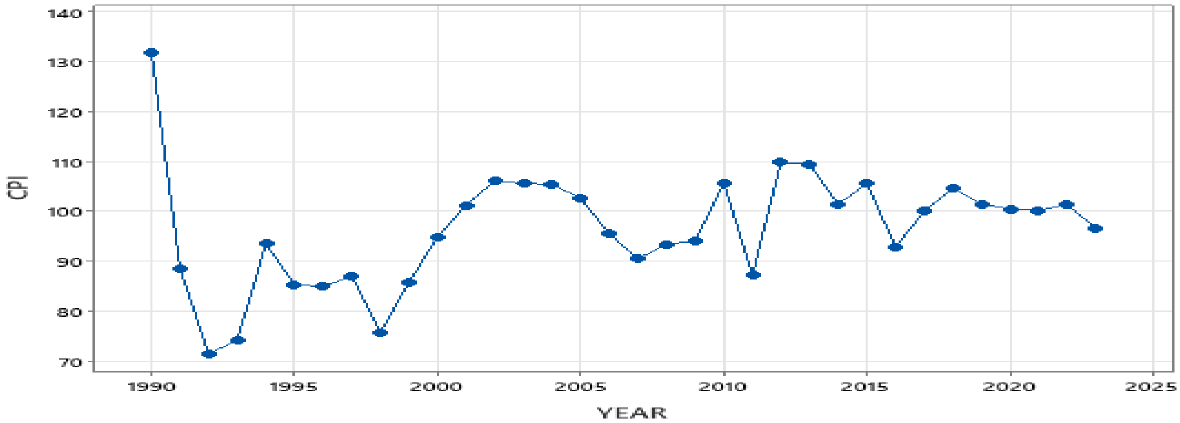

Figure 3: Time Series Plot for Crop Production Index (CPI) of Somalia

Exploratory Data Analysis and Diagnostic Test

Table 1: Summary Statistics, Using the Observations 1990 - 2023

Variables	Mean	Median	Min.	Max.	SD	IQR	Skewness	Kurtosis
GDP	5.1763	6.6944	-17.8470	23.6740	6.8745	4.2494	-0.6244	3.5982
CPI	96.6520	98.3410	71.4900	131.7700	11.6490	16.532	0.1939	1.2807
LPI	97.5960	98.6450	71.3300	110.2100	8.3508	7.8225	-1.1805	1.8243

Source: Gretl (32c) computation

Table 1 presents the summary statistics for Somalia's GDP, Crop Production Index (CPI), and Livestock Production Index (LPI) from 1990 to 2023. This descriptive statistics reveal substantial fluctuations in GDP, with high variability (SD = 6.8745) and leftward skewness (-0.6244), indicating economic instability. In contrast, the Crop Production Index (CPI) and Livestock Production Index (LPI) show more stable trends, albeit with occasional extreme values.

The study evaluates the assumption of normality in the time series data with the hypothesis of

H_0: The time series data follow normal distribution

H_1: The time series does not follow normal distribution

Table 2: Jarque-Bera Normality test

Variable	JB-Statistic	P-value	Decision
GDP Rate	20.5508	0.0000	Not Normally distributed

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Crop production index	2.5367	0.2813	Normally distributed
Livestock production index	12.6119	0.0018	Not Normally distributed

Footnote: JB = Jarque-Bera

The normality test in Table 2 above using the Jarque-Bera statistic confirms that GDP and LPI deviate significantly from normality leading to the rejection of normality at conventional significance levels, while CPI follows a normal distribution which fails to reject the normality assumption.

The Augmented Dicky Fuller (ADF) was employed to test whether the time series data is stationary or not. The hypothesis of the test is stated as:

H_0: The time series data is non-stationary

H_1: The time series data is stationary

Table 3: Augmented Dicky Fuller for Stationarity Test

Variable	ADF-Statistic	p-value	Order of Integration	Decision
GDP Rate	-3.9071	0.002***	(0): At level	Stationary
Crop production index	-4.6012	0.000***	(0): At level	Stationary
Livestock production index	-5.4843	0.000***	(1): 1st Diff.	Stationary

Footnote: ADF= Augmented Dickey Fuller

The results from the Augmented Dickey-Fuller (ADF) stationarity test in Table 3 indicate that the GDP rate and crop production index are stationary at their levels, as evidenced by their significant p-values (0.002 and 0.000, respectively). However, the livestock production index requires first differencing to become stationary, with its ADF statistic of -5.4843 and a p-value of 0.000.

Table 4: Breusch-Pagan test for Heteroskedasticity

Variable	Coefficient	Std. Error	t-ratio	p-value	Decision
Const	2.2963	4.5857	0.50008	0.6201	Not Significant
CPI	0.0383	0.0451	0.8484	0.4027	Not Significant
LPI	-0.0512	0.0629	−0.8135	0.4222	Not Significant
ESS	4.1706				
Test Statistics (LM)	2.0853				
P(Chi-square(2)	0.3525				

Footnote: ESS = Explained Sum of Squares

The Breusch-Pagan test for heteroskedasticity in Table 4 shows that all predictor variables (Crop Production Index, Livestock Production Index, and the constant term) have p-values greater than 0.05, indicating that none of them significantly contribute to heteroskedasticity. The test statistic (LM = 2.0853) and its associated p-value (0.3525) further confirm that the null hypothesis of homoskedasticity cannot be rejected. Therefore, the model does not exhibit significant heteroskedasticity, suggesting that the variance of the error terms remains constant.

Parameter Estimates and GARCH Model Identification

The study delves into the parameter estimates of the identified GARCH model, focusing into their implications for model performance and reliability. By examining these estimates, the aim to clarify how well the selected models capture the underlying volatility dynamics presents in the time series data.

Table 5: EGARCH (p, q) Models Parameter Estimates and Selection Criteria Values

Model	Parameter Estimates	P-values	Selection Criteria	Remark Suitable Model

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EGARCH (0,1)	$\hat{\mu}$ = 5.0606	0.0000	Llik: -106.6482	**EGARCH (0,1)**
	$\overline{\omega}$ = 4.0178	0.0000	AIC: 225.2964	
	α_1= -0.6552	0.3888	BIC: 234.2754	
	γ_1 = 1.0303	0.1342	HQC: 228.3175	

Based on the AIC, BIC, and HQC values as shown in Table 5 above, the EGARCH (0,1) model does not perform as well as the GARCH (1,2) model. While the EGARCH model is valuable for its ability to capture asymmetry and potentially model volatility clustering differently, the GARCH (1,2) model appears to be a better fit for the data given the selection criteria values.

Table 6: GARCH (p, q) Models Parameter Estimates and Selection Criteria Values

Model	**Parameter Estimates**	**P-Values**	**Selection Criteria**	**Remark Suitable Model**
GARCH (0,1)	$\hat{\mu}$ = 5.5634	0.0000	Llik: -106.1853	
	$\overline{\omega}$ = 6.3619	0.0894	AIC: 222.3705	
	α_1 = 2.2312	0.1346	BIC: 229.8531	
			HQC: 224.8882	
GARCH (0,2)	$\hat{\mu}$ = 7.6166	0.0000	Llik: -92.6014	
	$\overline{\omega}$ = 0.0653	0.2143	AIC:197.2028	
	α_1= 0.1647	0.2464	BIC:206.1819	
	α_2 = 3.1494	0.0957	HQC:200.2240	
GARCH (0,3)	$\hat{\mu}$ = 6.5289	0.0000	Llik: -93.8773	
	$\overline{\omega}$ = 0.0335	0.7135	AIC: 201.7546	
	α_1= 1.9483	0.0264	BIC:212.2302	
	α_2 = 0.4680	0.2464	HQC:205.2793	
	α_3 = 0.0193	0.0876		
GARCH (1,1)	$\hat{\mu}$ = 6.5402	0.0000	Llik: -94.1827	
	$\overline{\omega}$ = 0.0298	0.6680	AIC: 200.3654	
	α_1= 2.2804	0.0056	BIC:209.3444	
	β_1 = 0.1324	0.0277	HQC:203.3866	
GARCH (1,2)	$\hat{\mu}$ = 7.0464	0.0000	**Llik: -90.3202**	**GARCH (1,2)**
	$\overline{\omega}$ = 0.0000	1.0000	**AIC: 194.6404**	
	α_1= 0.0292	0.8066	**BIC: 205.1159**	
	α_2 = 3.6296	0.0214	**HQC: 198.1651**	
	β_1= 0.0032	0.9218		
GARCH (2,1)	$\hat{\mu}$ = 6.5368	0.0000	Llik: -93.4149	
	$\overline{\omega}$ = 0.0267	0.7161	AIC: 200.8298	
	α_1= 2.1493	0.0086	BIC: 211.3054	
	β_1 = 0.3305	0.0007	HQC: 204.3546	
	β_2= -0.0973	0.0944		
GARCH (2,2)	$\hat{\mu}$ = 6.5153	0.0000	Llik: -93.3174	
	$\overline{\omega}$ = 0.0000	1.0000	AIC: 202.6348	
	α_1= 1.4838	0.1307	BIC: 214.6069	
	α_2 = 0.8922	0.3029	HQC: 206.6630	
	β_1 = 0.1266	0.6455		
	β_2= -0.0758	0.2733		
GARCH (3,1)	$\hat{\mu}$ = 6.5491	0.0000	Llik: -93.2315	
	$\overline{\omega}$ = 0.0428	0.6807	AIC: 202.4630	
	α_1= 2.6019	0.0272	BIC:214.4351	
	β_1 = 0.2006	0.4165	HQC: 206.4913	
	β_2= -0.0279	0.7669		
	β_3= -0.0211	0.1525		

Based on the AIC, BIC and HQC values in Table 6 above, GARCH (1,2). is the most suitable model among those listed. It has the lowest AIC, BIC, and HQC values, indicating the best trade-off between fit and complexity.

Table 5: Taylor GARCH Models Parameter Estimates and Selection Criteria Values

Model	Parameter Estimates	P-values	Selection Criteria	Remark Suitable Model
Taylor/Schwert's GARCH (0,1)	$\hat{\mu}$ = 5.6284	0.0000	Llik: -105.7289	**Taylor GARCH (2,1)**
	$\overline{\omega}$ = 13.2201	0.0522	AIC: 221.4577	
	$\alpha_{1=}$ 1.2186	0.0467	BIC: 228.9403	
			HQC: 223.9754	
Taylor/Schwert's GARCH (0,2)	$\hat{\mu}$ = 6.5165	0.0000	Llik: -93.6489	
	$\overline{\omega}$ = 0.3579	0.7425	AIC: 199.2978	
	α_1= 0.9628	0.0198	BIC: 208.2768	
	α_2 = 0.6403	0.0358	HQC: 202.3189	
Taylor/Schwert's GARCH (0,3)	$\hat{\mu}$ = 7.2903	0.0000	Llik: -92.8792	
	$\overline{\omega}$ = 1.2845	0.1747	AIC: 199.7584	
	α_1= 0.2814	0.0209	BIC: 210.2339	
	α_2 = 1.5498	0.0014	HQC: 203.2831	
	α_3=-0.1132	0.1864		
Taylor/Schwert's GARCH (1,1)	$\hat{\mu}$ = 6.6748	0.0000	Llik: -95.2081	
	$\overline{\omega}$ = 0.8442	0.6367	AIC: 202.4162	
	α_1= 1.4182	0.0003	BIC: 211.3952	
	β_1 = 0.2271	0.0202	HQC: 205.4373	
Taylor/Schwert's GARCH (1,2)	$\hat{\mu}$ = 6.5178	0.0000	Llik: -93.6411	
	$\overline{\omega}$ = 0.3609	0.7325	AIC: 201.2822	
	α_1= 0.9712	0.0222	BIC: 211.7578	
	α_2= 0.6049	0.1608	HQC: 204.8069	
	β_1=0.0150	0.8493		
Taylor/Schwert's GARCH (2,1)	$\hat{\mu}$ = 6.8768	**0.0000**	**Llik: -89.3909**	
	$\overline{\omega}$ = 0.9596	**0.6719**	**AIC: 192.7819**	
	α_1= 1.4129	**0.0002**	**BIC: 203.2575**	
	β_1= 0.6005	**0.0000**	**HQC: 196.3066**	
	β_2= -0.2785	**0.0007**		

Based on the AIC, BIC and HQC values as shown in Table 4.7 above, Taylor/Schwert's GARCH (2,1). is the most suitable model among those listed. It has the lowest AIC, BIC, and HQC values, indicating the best balance between model fit and complexity.

Table 8: APARCH (p, q) Models Parameter Estimates and Selection Criteria Values

Model	Parameter Estimates	P-values	Selection Criteria	Remark Suitable Model
APARCH (1,1)	$\hat{\mu}$ = 6.5581	0.0000	Llik: -93.3469	**APARCH (2,1)**
	$\overline{\omega}$ = 0.0000	0.9911	AIC: 202.6939	
	α_1= 16.2494	0.9506	BIC: 214.6661	
	γ_1= -0.0703	0.7875	HQC: 206.7222	
	β_1= 0.0048	0.9720		
	δ_1 = 6.5713	0.8526		
APARCH (2,1)	$\hat{\mu}$ = 6.8731	0.0000	**Llik: -82.5729**	
	$\overline{\omega}$ = 10.5634	0.0000	**AIC: 183.1457**	
	α_1= 0.2512	0.0075	**BIC: 196.6143**	
	γ_1= 0.8113	0.0032	**HQC:187.6775**	
	β_1= 1.1909	0.0000		
	β_2= -0.6426	0.0000		
	δ_1 = 0.0433	0.3942		

Table 8 displays the parameter estimates and model selection criteria for APARCH (p, q) models, indicating the comparative suitability of APARCH (1,1) and APARCH (2,1) models. The APARCH (2,1) model shows a higher log-likelihood (-82.5729) and lower selection criteria values (AIC: 183.1457, BIC: 196.6143, HQC: 187.6775) compared to APARCH (1,1), suggesting it is a better fit for the data. Additionally, the parameters for APARCH (2,1), such as ω, α_1, γ_1, β_1, and β_2, are significant with p-values mostly below 0.01, further supporting its reliability. Consequently, APARCH (2,1) is identified as the suitable model for capturing volatility dynamics in this analysis.

Table 9: TARCH (p, q) Models Parameter Estimates and Selection Criteria Values

Model	Parameter Estimators	P-values	Selection Criteria	Remark Suitable Model
TARCH (0,1)	$\hat{\mu}$ = 5.1290	0.0000	Llik: -104.3656	**TARCH (0,2)**
	$\overline{\omega}$ = 15.6716	0.0001	AIC: 220.7311	
	α_1= 1.0355	0.0023	BIC: 229.7102	
	γ_1 = 0.4131	0.0746	HQC: 223.7523	
TARCH (0,2)	$\hat{\mu}$ = 6.5387	0.0000	**Llik: -88.3586**	
	$\overline{\omega}$ = 0.5794	0.7519	**AIC: 192.7172**	
	α_1= 1.3224	0.0684	**BIC: 204.6893**	
	α_2 = 0.4061	0.2366	**HQC: 196.7455**	
	γ_1 = -0.2423	0.2429		
	γ_2 = 1.7796	0.1650		
TARCH (1,1)	$\hat{\mu}$ = 6.6704	0.0000	Llik: -95.1875	
	$\overline{\omega}$ = 0.8698	0.3995	AIC: 204.3751	
	α_1= 1.3795	0.6232	BIC: 214.8506	
	γ_1 = 0.0516	0.9214	HQC: 207.8998	
	β_1= 0.2299	0.7714		
TARCH (1,3)	$\hat{\mu}$ = 6.8671	0.0000	Llik: -87.4345	
	$\overline{\omega}$ = 0.6989	0.1997	AIC: 196.8689	
	α_1= 0.5073	0.5357	BIC: 213.3305	
	α_2 = 1.1210	0.4008	HQC: 202.4078	
	α_3 = -0.8914	0.1194		
	γ_1 = 1.3366	0.3863		
	γ_2 = -0.1135	0.6655		
	γ_3 = 0.0331	0.8909		
	β_1= 0.5558	0.0000		

Among TARCH models fitted above in Table 9, the TARCH (0, 2) appears to be most suitable based on the following: It has the lowest AIC value of 192.7172, indicating the best balance between model fit and complexity. Its BIC and HQC values are also favorable compared to other TARCH models.

Table 6: NARCH (p, q) Models Parameter Estimates and Selection Criteria Values

Model	Parameter Estimates	P-values	Selection Criteria	Remark Suitable Model
NARCH (0,2)	$\hat{\mu}$ = 7.5679	0.0000	Llik: -92.2679	**NARCH (0,3)**
	$\overline{\omega}$ = 0.0000	0.9964	AIC:198.5359	
	α_1= 0.0086	0.9875	BIC:209.0114	
	α_2 = 25.7976	0.9820	HQC:202.0606	
	δ_1 = 5.3875	0.9415		
NARCH (0,3)	$\hat{\mu}$ = 7.0465	0.0000	**Llik: -87.8372**	
	$\overline{\omega}$ = 17.9863	0.0124	**AIC: 191.6744**	
	α_1= 0.3009	0.0582	**BIC: 203.6464**	
	α_2 = 0.5290	0.0090	**HQC: 195.7026**	
	α_3 = -0.1547	0.1809		
	δ_1 = 0.0939	0.8207		
NARCH (1,1)	$\hat{\mu}$ = 6.5064	0.0000	Llik: -93.4483	
	$\overline{\omega}$ = 0.0000	0.9907	AIC: 200.8966	
	α_1= 16.8440	0.9498	BIC: 211.3721	
	β_1= 0.0044	0.9730	HQC:204.4213	
	δ_1 = 6.3753	0.8544		

The above Table 10 compared the NARCH (p, q) models, the NARCH (0,3) emerges as the best suitable option. The NARCH (0, 3**),** exhibits the lowest AIC value of 191.6744, indicating the best trade-off between model fit and complexity among the models considered. Its BIC and HQC values, 203.6464 and 195.7026 respectively, are also lower than those of the other models, suggesting that its more parsimonious.

Table 7: GJR (p, q) Models Parameter Estimates and Selection Criteria Values

Model	Parameter Estimates	P-values	Selection Criteria	Remark Suitable Model
GJR (1,1)	$\hat{\mu}$ = 6.5683	0.0000	Llik: -94.1466	**GJR GARCH (1,2)**
	$\overline{\omega}$ = 0.0111	0.9020	AIC: 202.2931	
	α_1= 2.3630	0.0217	BIC: 212.7687	
	γ_1= -0.0624	0.8260	HQC:205.8178	
	β_1= 0.1405	0.0254		
	δ_1 = 0.0111	0.9020		
GJR (1,2)	$\hat{\mu}$ = 6.7103	0.0000	**Llik: -88.6687**	
	$\overline{\omega}$ = 0.2349	0.1653	**AIC: 195.3374**	
	α_1= 0.3516	0.0031	**BIC: 208.8059**	
	α_2 = 1.9502	0.1827	**HQC: 199.8691**	
	γ_1= 0.1608	0.2752		
	γ_2 = 1.1527	0.0000		
	β_1= -0.0142	0.0000		
	δ_1= 0.2349	0.1653		

Among the GJR models analyzed in the above Table 11, the GJR (1,2) model is the most suitable choice. This model achieves the lowest AIC value of 195.3374, indicating a better fit relative to its complexity. Its BIC and HQC values, 208.80593 and 199.8691 respectively, are also lower compared to the GJR (1,1) model, which has AIC, BIC, and HQC values of 202.2931, 212.7687, and 205.8178, respectively. The GJR (1,2) model displays more significant p-values for its parameters, with α_1, γ_2, and $\beta_1$being statistically significant, which contributes to its effective capture of the data's volatility dynamics.

Table 8: Fitted Models' Comparison

GARCH (p, p)	AIC	BIC	HQC	Log-likelihood
GARCH (0,1)	222.3705	229.8531	224.8882	-106.1853
GARCH (0,2)	197.2028	206.1819	200.2240	-92.6014
GARCH (0,3)	201.7546	212.2302	205.2793	-93.8773
GARCH (1, 1)	200.3654	209.3444	203.3866	-94.1827
GARCH (1, 2)	194.6404	205.1159	198.1651	-90.3202
GARCH (2, 1)	200.8298	211.3054	204.3546	-93.4149
GARCH (2, 2)	202.6348	214.6069	206.6630	-93.3174
GARCH (3, 1)	202.4630	214.4351	206.4913	-93.2315
EGARCH (0,1)	225.2964	234.2754	228.3175	-106.6482
TAYLOR (0,1)	221.4577	228.9403	223.9754	-105.7289
TAYLOR (0,2)	199.2978	208.2768	202.31896	-93.6489
TAYLOR (0,3)	199.7584	210.2339	203.2831	-92.8792
TAYLOR (1,1)	202.4162	211.3952	205.4373	-95.2081
TAYLOR (1,2)	201.2822	211.7578	204.8069	-93.6411
TAYLOR (2,1)	192.7819	203.2575	196.3066	-89.3909
TARCH (0,1)	220.7311	229.7102	223.7523	-104.3656
TARCH (0,2)	192.7172	204.6893	196.7455	-88.3586
TARCH (1,1)	204.3751	214.8506	207.8998	-95.1875
TARCH (1,3)	196.8689	213.3305	202.4078	-87.4345
APARCH (1,1)	202.6939	214.6661	206.7222	-93.3469
APARCH (2,1)	**183.1457**	**196.6143**	**187.6775**	**-82.5729**
NARCH (0,2)	198.5359	209.0114	202.0606	-92.2679
NARCH (0,3)	191.6744	203.6464	195.7026	-87.8372
NARCH (1,1)	200.8966	211.3721	204.4213	-93.4483
GJR (1,1)	202.2931	212.7687	205.8178	-94.1466
GJR (1,2)	195.3374	208.8059	199.8691	-88.6687

Table 12 presents the comparison of various volatility models based on Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Hannan-Quinn Criterion (HQC), and log-likelihood values. Among the models, APARCH (2,1) has the lowest AIC (183.1457), BIC (196.6143), and HQC (187.6775), along with a higher log-likelihood value (-82.5729), indicating its superior performance in capturing the data's volatility structure. Other models, such as TARCH (0,2) and TARCH (1,3), also show relatively low AIC and BIC values but do not surpass APARCH (2,1) across all selection criteria. Consequently, APARCH (2,1) emerges as the most suitable model for this dataset, balancing fit and model complexity effectively.

Forecast

Table 9: Forecast of the GDP Using the Identified APARCH (2,1) Model

Year	Forecasted GDP	Lower 95% CI	Upper 95% CI
2024	6.3109	-15.1789	16.7571
2025	6.3109	-15.6093	17.1876
2026	6.8109	-15.1961	16.774
2027	6.8109	-14.6403	16.2186
2028	6.3109	-14.3169	15.8951
2029	6.3109	-14.0453	15.6234
2030	5.7109	-13.8272	15.4054
2031	5.9109	-13.6823	15.2606
2032	5.9109	-13.8649	15.4432
2033	5.9109	-14.0129	15.5911
2034	5.9109	-14.0617	15.6399
2035	5.9109	-13.7482	15.3264
2036	5.9109	-13.5463	15.1245
2037	-3.4891	-13.5365	15.1147
2038	15.1109	-13.3503	14.9285
2039	22.9109	-13.5325	15.1107
2040	15.9109	-13.6512	15.2294
2041	8.7109	-13.4471	15.0253
2042	3.7891	-13.2872	14.8654
2043	4.3891	-13.3894	14.9676
2044	-1.8109	-13.5048	15.0829
2045	4.0891	-13.2889	14.8671
2046	3.1891	-13.5095	15.0877
2047	3.5891	-13.7035	15.2817

The forecasted GDP values using the APARCH (2,1) model in Table 13 above suggest a modest, generally positive economic outlook for Somalia's agro-economy, with GDP values fluctuating around a mean of 5-6% from 2024 to 2047. However, there are some years of anticipated volatility, including a steep decline in 2037 and an unexpected peak in 2039. The wide confidence intervals, particularly on the lower end, indicate considerable uncertainty, potentially due to economic or environmental instability impacting agriculture. This forecast underscores the need for sustainable policies and investment in agro-economic stability, as the broad variability in the confidence intervals points to external vulnerabilities, such as climate fluctuations or political factors, which could significantly affect Somalia's agro-economy in coming years.

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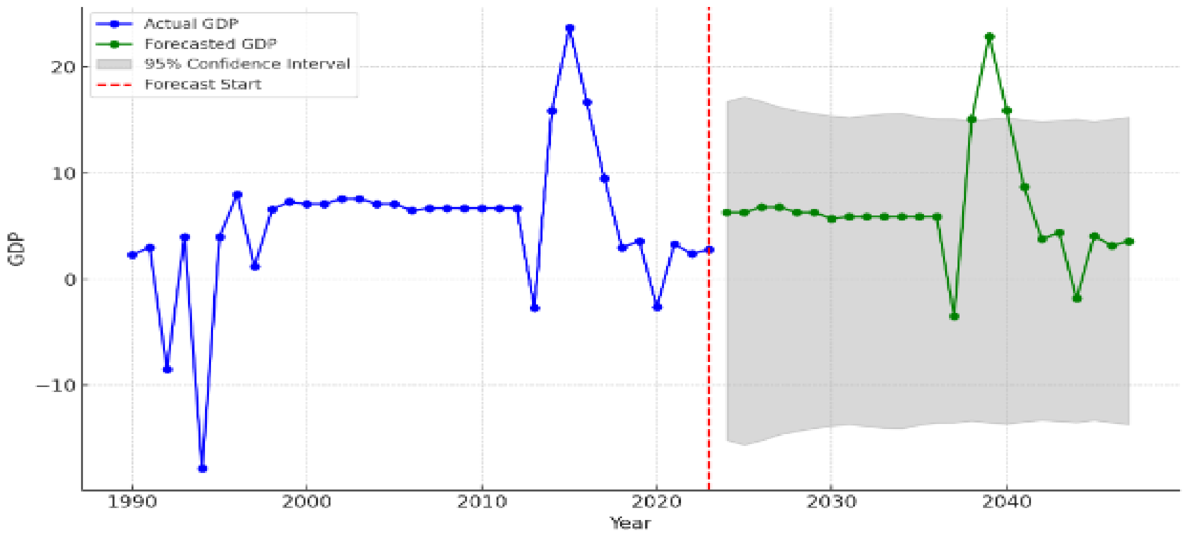

Figure 4: Forecast Plot for GDP of Somalia Agro-Economy using APARCH (2,1)

Discussion

The analysis of the time series plots revealed significant fluctuations in the livestock production index, crop production index, and GDP rate over the years. The year with the highest GDP rate was identified, aligning with periods of relative economic stability and favorable agricultural conditions. The Augmented Dickey-Fuller (ADF) test confirmed stationarity for GDP rate and crop production index at level form, while livestock production index became stationary after first differencing. These findings highlight the necessity of pre-processing economic time series data before modeling to ensure reliability in forecasting. Similar pre-processing techniques were adopted by Dinku (2021) in Ethiopia and Dessie et al. (2023) in their study on agricultural commodity price volatility, confirming that stationarity is a crucial prerequisite for volatility modeling in agro-economic datasets. The estimation of GARCH model parameters demonstrated that volatility clustering is present in Somalia's agro-economy, necessitating an advanced asymmetric model. The study compared different GARCH variants, with the APARCH (2,1) model emerging as the most suitable based on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). This aligns with findings from Nkpordee and Ogolo (2022), who applied GARCH models to assess economic accuracy in Nigeria, and Zhang and Chen (2020), who employed a copula-GARCH approach to model co-movements in agricultural commodity markets. Additionally, Dai et al. (2024) used a GJR-GARCH-MIDAS model to study geopolitical risks in international agriculture, reinforcing the importance of asymmetric GARCH models in capturing real-world volatility dynamics.

The forecasting results using the APARCH (2,1) model indicate a generally positive economic outlook for Somalia's agro-economy, with moderate fluctuations and occasional extreme values. However, the wide confidence intervals suggest uncertainty, emphasizing the need for robust economic policies and investment in agricultural resilience. Compared to the study by Dessie et al. (2023), which identified the EGARCH model as the most suitable for agricultural price volatility prediction, our findings suggest that APARCH (2,1) is better suited for Somalia's agro-economic context. This study provides critical insights into economic forecasting; reinforcing the role of advanced GARCH models in improving the accuracy of economic projections and policy formulation in agro-economically vulnerable regions.

Conclusion

This study successfully applied GARCH models to analyze volatility in Somalia's agro-economy, focusing on GDP rate, livestock production index, and crop production index. The findings revealed significant fluctuations, with notable peaks and declines, emphasizing the economic instability within the sector. The APARCH (2,1) model emerged as the most suitable for forecasting, providing insights into future economic trends despite the wide confidence intervals, which suggest potential external shocks. Compared to previous studies, such as those by Dinku (2021), Zhang and Chen (2020), which also employed GARCH models in agricultural markets, this study reaffirms the importance of volatility modeling in understanding economic behavior. The results underscore the need for proactive economic policies and investment strategies to enhance stability and resilience in Somalia's agricultural sector.

Recommendations

1. The Somali government and relevant stakeholders should establish a robust data collection framework to monitor agricultural production indices and GDP trends, ensuring timely policy responses to economic fluctuations.
2. Given the observed volatility in the agro-economy, policymakers should implement risk mitigation techniques such as crop diversification, price stabilization mechanisms, and climate adaptation strategies to minimize economic shocks.
3. Investments in modern agricultural technologies, infrastructure, and financial support for farmers should be prioritized to improve productivity and economic stability, aligning with the predictive insights from the identified APARCH (2,1) model.

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