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An ARCH-GARCH Approach to Paddy Production Volatility: A Seasonal Analysis of Monaragala District, Sri Lanka.

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Abstract

Paddy cultivation forms the backbone of Sri Lanka's agricultural economy and remains a vital pillar of national food security. However, fluctuations in paddy production, driven by climatic variability and other external factors, pose significant challenges to agricultural planning and policy formulation. This study investigates the volatility of paddy production in the Monaragala District, Sri Lanka, using annual production data for the Maha and Yala cultivation seasons spanning the period from 1960 to 2024. The analysis employs autoregressive (AR) models to estimate the conditional mean, followed by Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models to capture and forecast time-varying production volatility. The stationarity of the log-return series was confirmed using the Augmented Dickey–Fuller (ADF) test, while the ARCH–Lagrange Multiplier (ARCH-LM) test verified the presence of conditional heteroskedasticity in both seasonal series. The estimated results indicate that the two cultivation seasons exhibit distinct volatility characteristics. The Maha season is best represented by an AR(1)–ARCH(1) model, indicating short-term volatility persistence, whereas the Yala season is more appropriately modelled using an AR(2)–GARCH(1,1) framework, demonstrating substantial long-term volatility persistence ($\alpha + \beta = 0.8827$). These findings suggest that short-term crop insurance schemes may be effective in mitigating temporary climate-related risks during the Maha season, whereas reducing the highly persistent risks associated with the Yala season requires long-term structural interventions, including reservoir modernization and the rehabilitation of village tank cascade systems.

Keywords: ARCH-GARCH Models, Monaragala District, Paddy Production Volatility, Time Series Analysis, Yala and Maha Seasons

1. Introduction

1.1 Background of the Study

The agricultural sector remains a vital component of the Sri Lankan economy, contributing significantly to the Gross Domestic Product (GDP) and providing livelihoods for a substantial proportion of the rural population [7]. Within this sector, paddy (rice) cultivation occupies a position of exceptional importance. It serves not only as a major economic activity but also as an integral part of the country's cultural heritage, historical identity, and national food security strategy [5]. In Sri Lanka, rice cultivation is organized into two principal growing seasons: the Maha season, extending from September to March and primarily dependent on the northeast monsoon, and the Yala season, spanning from May to August and relying largely on the southwest monsoon together with irrigation systems [2].

The Monaragala District, located in the Uva Province, is an important agricultural region situated within Sri Lanka's dry and intermediate climatic zones. Consequently, agricultural production in the district is highly vulnerable to variations in weather conditions, particularly fluctuations in rainfall [5]. Although the district makes a substantial contribution to national paddy production, it also exemplifies the challenges faced by farming communities in climate-sensitive regions, where unpredictable fluctuations in annual production generate a series of economic and social consequences. These fluctuations affect farmers' incomes, regional food security, and the stability of industries that depend on agricultural production.

1.2 Problem Statement

The primary problem addressed in this study is the inherent volatility and unpredictability of paddy production. Conventional forecasting methods primarily focus on predicting production levels but often fail to adequately model and forecast production variability, or volatility. This volatility, characterized by periods of extreme and unexpected fluctuations in production, represents a critical source of risk that must be considered in agricultural planning and risk management [10]. For example, a bumper harvest followed by a year of severe crop failure presents significantly different policy challenges than a stable and predictable production pattern, even when the long-term average production remains unchanged. In a district such as Monaragala, which is particularly vulnerable to climatic hazards including droughts and floods, understanding the characteristics and persistence of production shocks is essential for effective agricultural management [2]. In addition to climatic influences, several operational and environmental factors affect agricultural productivity in the district, with climate-induced volatility further exacerbating these underlying uncertainties [9]. Consequently, effective agricultural planning and policy formulation require a robust statistical framework capable of modelling and forecasting time-varying production volatility.

1.3 Research Objectives

The primary objective of this study is to model and forecast the volatility of paddy production in the Monaragala District for both the Maha and Yala cultivation seasons. To achieve this objective, the following specific objectives were formulated:

- To analyse the historical trends and statistical characteristics of paddy production in the Monaragala District over the period from 1960 to 2024.
- To identify an appropriate time series model for the conditional mean of the paddy production growth rate.
- To examine the presence of Autoregressive Conditional Heteroskedasticity (ARCH) effects in the production data, thereby establishing the suitability of volatility modelling.
- To estimate appropriate ARCH/GARCH models for capturing the time-varying volatility of paddy production during both the Maha and Yala cultivation seasons.
- To interpret the estimated model results and discuss their implications for agricultural policy formulation and production risk management in the Monaragala District.

1.4 Significance of the Study

This research contributes to the existing literature by applying a sophisticated econometric technique, the ARCH/GARCH model, to a specific and critical area of Sri Lankan agriculture. The findings are significant for several stakeholders. For government bodies and policymakers, such as the Ministry of Agriculture and the Hector Kobbekaduwa Agrarian Research and Training Institute (HARTI), the study provides a scientific framework for forecasting production volatility. This can aid in the strategic management of food reserves, the planning of import/export policies, and the design of more effective crop insurance schemes. For farmers and agricultural organizations in the Monaragala district, an understanding of volatility patterns can inform decisions related to resource allocation and risk mitigation. Finally, from an academic perspective, this study provides a methodological precedent for applying volatility models to other crops and regions within Sri Lanka, filling a gap in the empirical literature.

1.5 Literature Review

A literature review serves to situate the current study within the existing body of scholarly work, identifying the theoretical foundations and empirical precedents that inform the research. This review begins by outlining the theoretical framework of time series volatility models, then discusses their application in agricultural contexts, and finally narrows the focus to paddy forecasting in Sri Lanka to identify the specific research gap that this paper aims to fill.

1.5.1 Theoretical Framework of Time Series Volatility Modelling

Time series analysis provides a robust framework for understanding and forecasting data points collected over time [1]. For many economic and agricultural series, a common assumption of classical regression is that the variance of the error term is constant, or homoscedastic. In practice, however, this assumption is generally not observed. Most financial and economic time series show periods of high volatility and periods of relative stability, which is referred to as volatility clustering [4].

To solve this, in his seminal paper published in 1982, Robert F. Engle proposed the Autoregressive Conditional Heteroskedasticity (ARCH) model [8]. This was a groundbreaking way of modelling, as it considered the variance to be conditional and time-changing. The basic concept of the ARCH model is that the variance of the error term at a certain time depends upon the magnitude of the error terms from previous periods [8]. In particular, the ARCH(q) model defines the conditional variance as a linear equation of the previous q squared error terms. This enables the model to explain the tendency for large shocks (positive or negative) to be succeeded by other large shocks, and for small shocks to be succeeded by other small shocks.

Although the ARCH model was pioneering, it tended to require an excessively large number of lags (q). To address this shortcoming, Tim Bollerslev (1986) came up with the Generalized ARCH (GARCH) model (Bollerslev, 1986). The GARCH model builds on the ARCH model and allows the current conditional variance to depend on its own past values as well as past squared error terms. The most widely used specification, the GARCH (1, 1) model, has one ARCH term and one GARCH term, making it more parsimonious than a high-order ARCH model [3]. These models are described in standard econometrics textbooks, which explain their specification, estimation, and interpretation [4].

1.5.2 Empirical Applications in Agriculture

ARCH/GARCH models have been extensively applied to the analysis of commodity price volatility in agricultural economics and have subsequently been used to examine other types of volatility. For example, [10] established that GARCH models were very effective in forecasting volatile agricultural prices in India compared to simpler models such as ARIMA, indicating that agricultural markets were highly erratic [10]. Closer to the topic of the present research, these models have also been used to predict volatility in crop yield. The GARCH models employed in [11] to predict wheat yield volatility in a semi-arid region were found to be effective in forecasting volatility under climatic conditions similar to those of Sri Lanka's dry zone [11]. In their study, they demonstrated that GARCH models were capable of effectively capturing uncertainty in crop production caused by environmental factors.

Similarly, nonlinear time series models have been used to predict the complex production patterns of oil palm in India, supporting the idea that simple linear models are not always suitable for agricultural data [13].

1.5.3 Context of Paddy Forecasting in Sri Lanka

Time series analysis has been used as an agricultural forecasting tool in Sri Lanka. ARIMA models were used by [6] to predict paddy production in another major paddy-producing region in the dry zone, the Anuradhapura District, providing a solid methodological precedent for the current study [6]. Similarly, ARIMA models have also been employed to forecast the prices of other agricultural products, such as vegetables, in Sri Lanka.

Nevertheless, much of the literature recognizes that paddy production in Sri Lanka is strongly affected by several influencing factors, the most prominent of which is climate. Similar empirical efforts in South Asia have evaluated the predictive suitability of climatic parameters on major regional crops to anticipate production outcomes [12]. The study by [2] examined the effects of climate change on paddy production and the direct effects of temperature and precipitation on paddy yield. Studies conducted in the dry zone, where Monaragala is located, have focused on issues related to water shortages and dependence on monsoon rainfall, which are key contributors to production shocks [5].

In spite of this body of work, there is an evident research gap. Although ARIMA models have been applied to forecast production levels, the use of ARCH/GARCH models specifically to measure and forecast the volatility of paddy production at the district level in Sri Lanka is not well documented. The purpose of this paper is to address that gap by explicitly modelling the risk and uncertainty of paddy production in this critical district using the ARCH/GARCH framework.

2. Methodology

Figure 1 presents the methodological framework adopted for the time-series analysis and volatility modelling of paddy production. The framework illustrates the sequential procedures undertaken prior to model estimation, including data preparation, assessment of normality, evaluation of stationarity using the Augmented Dickey–Fuller (ADF) test, and examination of autocorrelation. These procedures were followed by the specification of the conditional mean equation and the assessment of conditional heteroskedasticity using the ARCH–Lagrange Multiplier (ARCH-LM) test, followed by the estimation and comparison of appropriate ARCH and GARCH models for the Maha and Yala seasons.

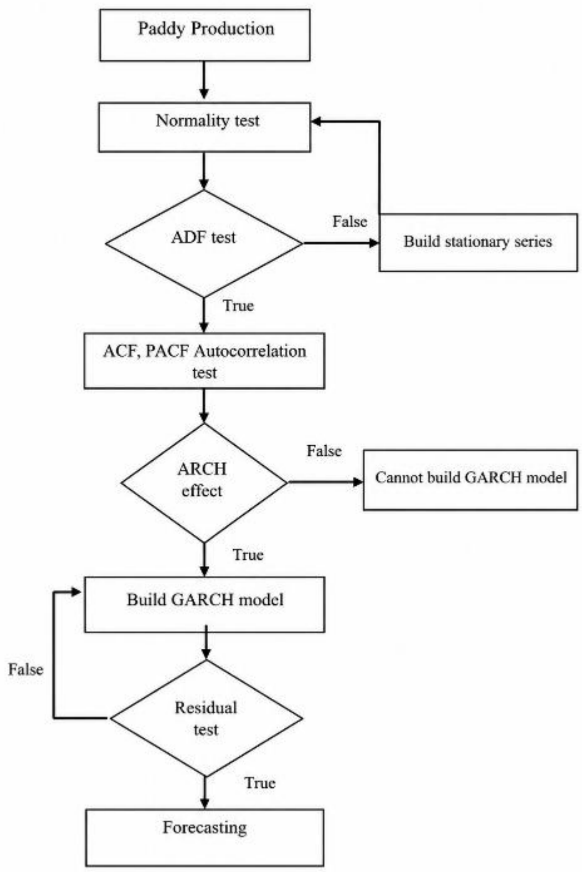

Fig. 1. Research Diagram

2.1 Data Source and Preparation

The study utilized secondary time-series data on annual paddy production in the Monaragala District of Sri Lanka covering the period from 1960 to 2024. The data were obtained from the Department of Census and Statistics and were categorized according to the two principal cultivation seasons, namely, Maha and Yala. Paddy production was measured in thousands of metric tons ('000 MT).

Some missing observations were identified in the Maha season dataset. To maintain a continuous time series required for ARCH modelling, the missing values were

estimated using linear interpolation based on the observations from the preceding and succeeding years. In contrast, the Yala season dataset was complete and contained no missing observations.
To analyze production volatility, the raw annual production series (p_t) was transformed into a log-return series (r_t) using the following formula:

$$r_t = \ln(p_t) - \ln(p_{t-1}) \quad (1)$$

While agricultural production series often exhibit trend-stationarity rather than the stochastic trends typical of financial assets, the log-return transformation is utilized here for variance stabilization, growth rate interpretation and stationarity. Analysis was done in E Views 10.

2.2 Model Specification

The econometric analysis follows a multi-stage process to model the conditional mean and time-varying volatility of paddy production growth rates in the Monaragala district.

Before modeling volatility, the stationarity of the log-return series (r_t) was verified using the Augmented Dickey-Fuller (ADF) test. To isolate the annual production shocks (residuals), a mean equation was specified as follows:

$$r_t = \mu + \epsilon_t \quad (2)$$

Where:
r_t : The log-return of paddy production at time t
μ : Constant mean growth rate.
ϵ_t : Production shock

2.2.1 Conditional Mean Equation

To isolate the annual production shocks and filter out any low-order serial dependencies, time-varying Autoregressive AR (p) processes were specified for the conditional mean.

A first-order autoregressive (AR (1)) mean structure was specified for the Maha season.

$$\boldsymbol{r_{Maha,t} = \mu + \emptyset_1 r_{Maha,t-1} + \epsilon_t} \quad (3)$$

A second-order autoregressive (AR (2)) mean structure was specified for the Yala season.

$$\boldsymbol{r_{Yala,t} = \mu + \emptyset_1 r_{Yala,t-1} + \emptyset_2 r_{Yala,t-2} + \epsilon_t} \quad (4)$$

Where,
$\boldsymbol{r_t}$: Log returns of paddy production at time t.
$\boldsymbol{\mu}$ **:** Constant baseline mean growth rate
$\emptyset_1$: First-order autoregressive parameter
$\emptyset_2$: Second-order autoregressive parameter
$\boldsymbol{\epsilon_t}$: Production Shock

The residuals $(\boldsymbol{\epsilon_t})$ extracted from these mean specifications were subjected to an ARCH Lagrange Multiplier (ARCH-LM) test at lag 1 to verify the presence of conditional heteroskedasticity (volatility clustering).

2.2.2 Conditional variance equations

Autoregressive Conditional Heteroskedasticity frameworks were specified to capture the dynamic evolution of production risk. The general unconstrained baseline model is specified as a GARCH (1, 1) process.

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (5)$$

Where,
σ_t^2 : Conditional variance of paddy production at time t.
ω : Long-term baseline variance constant
α : ARCH parameter
β : GARCH parameter

A restricted variation of this framework is employed alongside the unconstrained model to safeguard parameter validity against potential sample limitations and over-parameterization. The system collapses into a parsimonious ARCH (1) structure by explicitly constraining the GARCH parameter to zero (β=0).

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 \quad (6)$$

3. Results

This section presents the empirical results of the time series analysis conducted for both the Maha and Yala paddy production seasons in the Monaragala district.

3.1. Analysis of the Maha Season

3.1.1. Stationarity and ARCH Effect Test

Fig. 2. presents the time-series plot of Maha-season paddy production in the Monaragala District from 1960/1961 to 2023/2024. The series exhibits a clear long-term upward stochastic trend over the study period, with periodic peaks suggesting possible cyclical or seasonal variations. These characteristics indicate that the Maha-season paddy production series is non-stationary, as evidenced by the pronounced upward trend and changing variance over time. To further confirm the non-stationarity of the raw Maha-season paddy production data, the Augmented Dickey–Fuller (ADF) test was conducted.

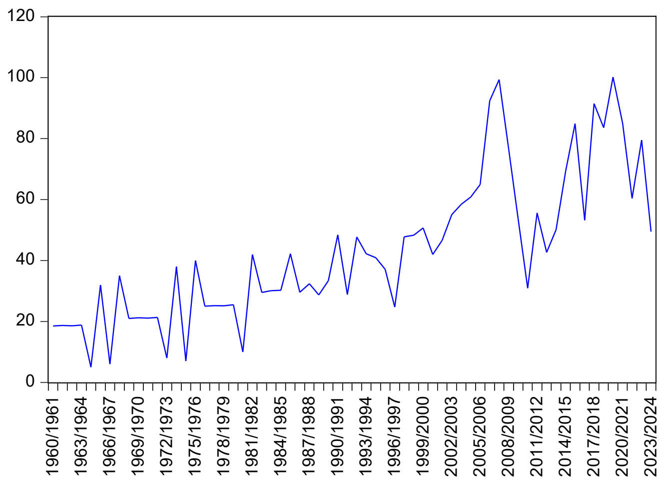

Fig. 2. Time Series plot of paddy production ('000 MT) in Maha season

Table 1
ADF Test of paddy production in Maha Season

Test Statistic	Value	Probability
Augmented Dickey-Fuller	-1.7708	0.3914

Table 1 presents the results of the ADF test for the Maha-season paddy production series in the Monaragala District. The results confirm that the series is non-stationary, with a p-value of 0.3914, which is statistically insignificant at the 5% significance level. Therefore, the null hypothesis of a unit root cannot be rejected, indicating the presence of non-stationarity in the original paddy production series. To address the non-stationarity of the paddy production data, the series was transformed into a log-return series, denoted as r_maha and the ADF test was subsequently applied to the transformed series.

Table 2
ADF Test of Maha Season log returns (r_maha)

Test Statistic	Value	Probability
Augmented Dickey-Fuller	-6.0106	0.0000

Table 2 presents the results of the ADF test for the Maha season log-return series. The results confirm that the log-return series is stationary, as indicated by the highly significant p-value ($p < 0.001$).

Based on the correlogram analysis of the log-return series, an AR (1) structure was identified as the appropriate specification for the conditional mean equation. The AR (1) model was selected based on the statistical significance of its parameter ($p < 0.001$) and the Akaike Information Criterion (AIC = 1.2931). Higher-order autoregressive and moving-average terms were found to be statistically insignificant; therefore, the AR (1) structure was considered the most appropriate specification for the conditional mean equation. Following the filtering of the conditional mean using an AR (1) process, an ARCH Lagrange Multiplier (ARCH-LM) test was conducted at lag 1 to assess the presence of conditional heteroskedasticity, or volatility clustering, in the residual series.

Table 3
ARCH-LM Test on Residuals of Maha Mean Equation

Statistic	Value	Probability
F-statistic	4.0634	0.0483
Obs*R-squared	3.9325	0.0474

Table 3 presents the results of the ARCH-LM test. The p-values for both the F-statistic (0.0483) and the Obs*R-squared statistic (0.0474) are below the 5% significance threshold. Therefore, the null hypothesis of no ARCH effects is rejected at the 5% significance level. This finding provides evidence of conditional heteroskedasticity, indicating the presence of time-varying volatility clustering in the residuals of the Maha-season paddy production series.

Table 4
ARCH (1) Model Estimation Results for Maha Season

Variable	Coefficient	Std. Error	z-Statistic	Probability
		Mean Equation		
C	0.0046	0.0467	0.0993	0.9209
AR(1)	-0.6242	0.0979	-6.3756	0.0000
		Variance Equation		
C (ω)	0.1436	0.0283	5.0841	0.0000
RESID(-1)^2 (α)	0.2445	0.3335	0.7333	0.0483

Table 4 presents the estimation results of the AR (1)-ARCH (1) model. In the conditional mean equation, the AR (1) parameter is highly significant ($p < 0.001$). Similarly, the baseline volatility constant (ω) in the conditional variance equation is highly significant ($p < 0.001$). The estimated ARCH parameter (α), which captures the short-term impact of volatility shocks, is statistically significant at the 5% significance level ($p = 0.0483$).

3.1.2. GARCH Model Estimation for Maha Season

Based on the significant ARCH-LM test, a GARCH (1, 1) model was estimated. The results are presented in Table 3.

Table 5
GARCH (1, 1) Model Estimation Results for Maha Season

Variable	Coefficient	Std. Error	z-Statistic	Probability
		Mean Equation		
C	0.03175	0.0274	1.1574	0.2471
AR(1)	-0.5380	0.0002	-27.271	0.000
		Variance Equation		
C (ω)	0.00284	0.0040	0.7176	0.4730
RESID(-1)^2 (α)	-0.1533	0.0773	-1.9840	0.0473
GARCH (-1) (β)	1.1483	0.0903	12.7190	0.0000

Table 5 presents the estimation results of the unconstrained AR (1)-GARCH (1, 1) model for the paddy production log-return series. Although the GARCH (1, 1) model yields a highly significant GARCH (−1) parameter ($\beta=1.1483$, $p<0.001$), this result is not structurally valid because the estimated ARCH parameter ($\alpha=-0.1533$, $p=0.0473$) is negative. This violates the fundamental non-negativity constraints required for a valid conditional variance specification. Therefore, there is no need to assess the sum of the ARCH and GARCH coefficients; the negative ARCH parameter alone is sufficient to disqualify the unconstrained GARCH (1, 1) model from further practical consideration.

3.1.3. Model Comparison Summary

Table 6 presents a comparison of the AR (1)-ARCH (1) and AR (1)-GARCH (1, 1) models. The GARCH (1,1) model failed to satisfy the fundamental theoretical constraints of time-series econometrics, as indicated by the estimated negative ARCH coefficient ($\alpha=-0.1533$). This negative coefficient renders the unconstrained GARCH (1, 1) specification structurally invalid. Consequently, evaluating the joint parameters or the sum of the ARCH and GARCH coefficients is not theoretically meaningful, as the model estimation does not provide a valid conditional variance process. Therefore, the unconstrained GARCH (1, 1) model was discarded, and the AR (1)-ARCH (1) model was selected as the most appropriate specification for the Maha-season paddy production series.

Table 6
Model comparison of AR (1)-ARCH (1) and AR (1)-GARCH (1, 1)

Evaluation Metric	AR(1)-ARCH(1)	AR(1)-GARCH(1,1)
Mean constant (c)	0.0046 ($p=0.9209$)	0.0318 ($p=0.2471$)
AR(1) coefficient (ϕ)	-0.6242 ($p<0.001$)	-0.5380 ($p<0.001$)
Variance Coefficient(ω)	0.1436 ($p<0.001$)	0.0028 ($p=0.4730$)
ARCH Parameter (α)	0.2446 ($p=0.0483$)	-0.1533 ($p=0.0473$)
GARCH Parameter(β)	Constrained to 0	1.1483 ($p<0.001$)
Log likelihood	-35.4249	-25.9450
AIC	1.0718	0.9982
Durbin Watson	2.6207	2.7862
Adjusted R^2	0.5402	0.5101

3.2. Analysis of the Yala Season

3.2.1. Stationarity and ARCH Effect Test

Fig.3. presents the time-series plot of Yala season paddy production in the Monaragala District from 1960 to 2024. The series exhibits a clear non-linear, U-shaped historical trend, indicating that the series is non-stationary in its mean. To further confirm the non-stationarity of the raw Yala-season paddy production data, the Augmented Dickey–Fuller (ADF) test was conducted.

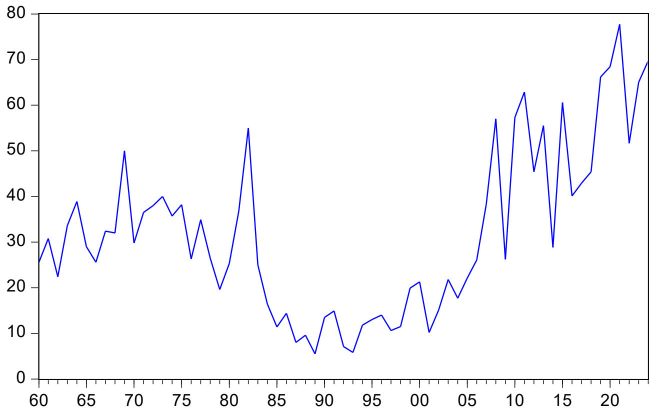

Fig.3. Time Series plot of paddy production in Yala season

Table 7

ADF Test of paddy production in Yala Season

Test Statistic	Value	Probability
Augmented Dickey-Fuller	-1.1803	0.6779

Table 7 presents the results of the ADF test for the Yala-season paddy production series in the Monaragala District. The results confirm that the series is non-stationary, with a p-value of 0.6779, which is statistically insignificant at the 5% significance level. Therefore, the null hypothesis of a unit root cannot be rejected, indicating the presence of non-stationarity in the original paddy production series. To address the non-stationarity of the paddy production data, the series was transformed into a log-return series, denoted as r_yala , and the ADF test was subsequently applied to the transformed series.

Table 8

ADF Test of Yala Season log returns (r_yala)

Test Statistic	Value	Probability
Augmented Dickey-Fuller	-10.8778	0.0000

Table 8 presents the results of the ADF test for the Yala season log-return series. The results confirm that the log-return series is stationary, as indicated by the highly significant p-value ($p < 0.001$).

Based on the correlogram analysis of the log-return series, the appropriate structure for the conditional mean equation was determined. Although both the AR (1) and AR (2) models were statistically significant, the AR (2) specification was selected as the preferred model because it achieved lower values for both the Akaike Information Criterion (AIC = 0.9395) and the Hannan–Quinn criterion (HQ = 0.9927), together with a superior log-likelihood value.

Table 9

Comparison of AR (1) model and AR (2) model

Statistical Criterian	AR(1)	AR(2)
AIC	0.9609	0.9395
Hannan-Quinn criterion	1.0008	0.9927
Log-Likelihood	-27.7500	-26.0650
Adjusted R^2	0.0721	0.1065
Durbin-Watson Stat	2.1470	2.1140

The AR (2) model is selected as the optimal conditional mean equation. Following the filtering of the conditional mean using an AR (2) process, an ARCH Lagrange Multiplier (ARCH-LM) test was conducted at lag 1 to assess the presence of conditional heteroskedasticity, or volatility clustering, in the residual series.

Table 10

ARCH-LM Test on Residuals of Yala Mean Equation

Statistic	Value	Probability
F-statistic	5.0626	0.0281
Obs*R-squared	4.8279	0.0280

Following the estimation of the AR (2) conditional mean equation for the Yala season, an ARCH-LM test was conducted at lag 1 to test the presence of the time-varying volatility clustering (conditional heteroskedasticity) in the residuals.

Table 10 presents the results of the ARCH-LM test. The p-value of the test statistic (0.0281) is below the 5% significance level, leading to the rejection of the null hypothesis of homoscedastic residual variance. Similarly, the Obs*R-squared statistic is statistically significant, with a p-value of 0.0280. These results provide evidence of conditional heteroskedasticity, indicating the presence of time-varying volatility clustering in the residuals of the Yala season paddy production series.

Table 11

ARCH (1) Model Estimation Results for Yala Season

Variable	Coefficient	Std. Error	z-Statistic	Probability
		Mean Equation		
C	0.0129	0.0289	0.4447	0.6565

AR(1)	-0.4336	0.1354	-3.2029	0.0014
AR(2)	-0.2185	0.1126	-1.9391	0.0425
		Variance Equation		
C (ω)	0.1003	0.0332	3.0192	0.0025
RESID(-1)^2 (α)	0.2461	0.2869	0.8578	0.0210

Table 11 presents the estimation results of the AR (2)-ARCH (1) model for the Yala-season paddy production series. In the conditional mean equation, both the first-order ($\phi 1=-0.4336$, $p=0.0014$) and second-order ($\phi 2=-0.2185$, $p=0.0425$) autoregressive coefficients are statistically significant. In the conditional variance equation, the baseline volatility constant ($\omega=0.1003$, $p=0.0025$) is statistically significant, while the ARCH shock parameter ($\alpha=0.2461$) is also statistically significant at the 5% level ($p=0.0210$).

3.2.2. GARCH Model Estimation for Yala Season

Based on the significant ARCH-LM test, a GARCH (1, 1) model was estimated. The results are presented in Table 12.

Table 12
GARCH (1, 1) Model Estimation Results for Yala Season

Variable	Coefficient	Std. Error	z-Statistic	Probability
		Mean Equation		
C	0.0219	0.0270	0.8105	0.4176
AR(1)	-0.4541	0.1371	-3.3131	0.0009
AR(2)	-0.2294	0.1278	-1.7945	0.0427
		Variance Equation		
C (ω)	0.0162	0.0291	0.5558	0.5784
RESID(-1)^2 (α)	0.1710	0.1932	0.8848	0.0376
GARCH(-1) (β)	0.7117	0.3193	2.2286	0.0258

Table 12 shows that the output of AR (2)-GARCH (1, 1) model, that was estimated for the Yala season paddy production log-returns. In the estimated conditional mean equation, the first-order autoregressive coefficient (ϕ_1) and the second-order autoregressive coefficient (ϕ_2) are statistically significant at 5% significance level with p values of 0.0009 and 0.0427 respectively. In the conditional variance equation, the ARCH parameter (α), is 0.1710.
It displays statistical significance at 5% significance level ($p = 0.03763$), The GARCH parameter (β) is estimated at 0.7117 and is highly significant at the 5% level ($p = 0.0258$). Because the sum (α+ β) is strictly less than 1, the estimated system complies fully with the dynamic stability and covariance stationarity requirements.

3.2.3. Model Comparison Summary

Table 13
Model comparison Of AR (2)-ARCH (1) and AR (2)-GARCH (1, 1)

Evaluation Metric	AR(2)-ARCH(1)	AR(2)-GARCH(1,1)
Mean constant (c)	0.0129 ($p = 0.6565$)	0.0219 ($p = 0.4176$)
AR(1) coefficient (ϕ_1)	-0.4336 ($p = 0.0014$)	-0.4541 ($p = 0.0009$)
AR(2) coefficient (ϕ_2)	-0.2185 ($p = 0.0425$)	-0.2294 ($p = 0.0427$)
Variance Coefficient(ω)	0.1003 ($p = 0.0025$)	0.0162 ($p = 0.5784$)
ARCH Parameter (α)	0.2461 ($p = 0.0210$)	0.1710 ($p = 0.0376$)
GARCH Parameter(β)	None	0.7117 ($p = 0.0258$)
Volatility Persistence	α = 0.246	α+ β= 0.8827
Log likelihood	-24.6018	-23.5127
AIC	0.9549	0.9520
BIC	1.1264	1.1579
Durbin Watson	1.985	1.949

Table 13 shows that the comparison of the AR (2)-ARCH (1) model and AR (2)-GARCH (1, 1) to determine the best model for the Yala season paddy production returns. AR (2)-GARCH (1, 1) model achieves a superior Log-Likelihood (-23.5127) and minimizes the Akaike

Information Criterion (AIC = 0.9520) relative to the ARCH framework. AR(2)-GARCH(1,1) shows that Yala production shocks have a strong, long-term memory of 88.27%, meaning output fluctuations linger across multiple years before returning to average levels. Therefore, the AR (2)-GARCH (1, 1) model can be considered as the best model.

4. Discussion

The empirical investigation into the volatility of paddy production in the Monaragala district from 1960 to 2024 yielded several conclusive findings. After confirming the stationarity of the log-return series for both Maha and Yala seasons, the study established the significant presence of Autoregressive Conditional Heteroskedasticity through the ARCH-LM test. This justified the use of a GARCH model to explain the variation of production volatility with time.

4.1. Cyclical Adaptations and Mean-Reverting Patterns

It included highly significant autoregressive components with different lag structures in the conditional mean equations of both seasons. For the Maha season first order autoregressive process (AR (1) = -0.624241, $p<0.001$) and for the Yala season second order autoregressive process (AR (1) = -0.4541, $p=0.009$ AR (2) = -0.2294, $p= 0.0427$) have estimated.

The negative coefficients of each AR terms across both seasons indicate a self-correcting powerful cyclical behaviour in paddy yields. It is typical for the systems responding resource constraints and market signals in agricultural economics.

4.2. Comparative Volatility profiles and Risk Persistence

Here is the way how production risks persist over time between the two seasons.

- Maha Season: AR(1)-ARCH(1) - Short-term shock memory ($\alpha = 0.2446$)
- Yala Season: AR(2)-GARCH(1,1) – Long-term risk persistence.($\alpha + \beta = 0.8827$)

AR (1)-ARCH (1) framework is the best model for the Maha season. The positive coefficient of the estimated ARCH parameter ($\alpha = 0.2446$) satisfies the theoretical non-negativity constraint required for conditional variance modelling. It captures the short-term impact of volatility shocks.

The magnitude of, indicates that approximately 24.46% of any unexpected production shock (eg: Severe weather volatility of sudden policy changes) translates directly into next year's production variance.

In contrast, the Yala season behaves as a highly persistent, long memory risk system modelled by an AR (2)-GARCH (1, 1) as the best model. The immediate shock impact ($\alpha = 0.1710$) and the GARCH parameter ($\beta=0.7117$, $p=0.0258$) are highly significant, proving that Yala season production risk has a long-term memory component. The sum of the variance coefficients ($\alpha + \beta = 0.8827$) is less than 1, confirming that the volatility process is mean-reverting. This indicates that the localized agricultural shocks have a highly persistent impact on production risk.

4.3. Agricultural Policy and Water Management Implications

The several types risks behave in Maha season and Yala season by providing important insights for local climate adaptation plans. The Maha season takes place during the heavy northeast monsoon rains. This means that even if one Maha season is poor, the heavy rainfall in the next cycle usually helps the region recover quickly.

The Yala season takes place during the dry period. It depends heavily on smaller irrigation systems that connected with village tank systems and water left over from the previous Maha season. When a major drought or water shortage hits a Yala cycle, the damage spills over into future years. Dried-out soil and low reservoir levels carry over directly into the next dry seasons. This explains why the Yala system holds onto roughly 88.27% of past risk and instability. Production drops in the Yala season tend to plague the district for multiple years before returning to normal.

5. Conclusion

This study successfully modelled the time-varying volatility and production dynamics of paddy yields in the Monaragala district across its two main cultivation seasons, Maha and Yala from 1960 to 2024. By implementing autoregressive conditional heteroskedasticity models, the findings revealed that structural gaps in understanding seasonal agricultural risk structures.

The findings reveal that returns of paddy production in both seasons exhibit self-correcting, mean-reverting cyclical behaviours.

The Maha season is captured by an AR (1)-ARCH (1) framework, where the volatility is driven by immediate, short-term climate variability that transmit roughly 24.5% of their shock variance into the next year before rapidly dispelling.

The Yala season is best defined by an AR (2)-GARCH (1, 1) model. Shocks in the Yala season include an extensive memory effect of 88.27% reflecting a highly persistent lingering impact on production risk in Yala season.

To protect farmers from sudden shocks during the rainy Maha season, Short-term crop insurance works well enough. However, stabilizing the dry Yala season requires long-term, structural policies. These fixes include modernizing small reservoir networks, repairing ancient village tank cascades to survive multi-year droughts, and introducing drought-resistant rice varieties. Taking these steps will break the cycle and protect modern crop yields from past water shortages.

6. Limitations

This study, while providing valuable insights, has certain limitations.

- Sample Size and Data Constraints: This study relies on a moderate sample size with 64 observations. While this timeframe is sufficient to achieve maximum likelihood for the structural frameworks used, the sample size limits the integration of higher order extensions like EGARCH or TGARCH models.
- Exclusion of Exogenous variables: In this study the variance equations are strictly endogenous relying entirely on historical production logs (α and β terms) to observe conditional volatility. It does not include exogenous variables that are known to affect production such as rainfall data, temperature, fertilizer policies or government subsidy policies.
- Spatial Aggregation: This study uses district level data for Monaragala. This high-level view might hide local differences in weather, soil quality, and irrigation setups across the smaller farming zones within the district.

A notable limitation of the current study is its reliance on a univariate autoregressive conditional variance framework. While the optimized ARCH and GARCH structures successfully capture the aggregate mathematical footprint of time-varying production risk, they do not explicitly disaggregate external environmental covariates. Because climate variability remains the central driver of dry-zone production variance, a highly constructive pathway for future research lies in expanding this framework into a multivariate GARCH-X structure.

Competing Interests

The authors have no competing interests to declare

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