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Time series modeling and forecasting of Maha season paddy production in Monaragala district using ARCH-GARCH models

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Abstract

Paddy cultivation constitutes the backbone of Sri Lanka's agricultural economy and remains a crucial pillar of national food security. However, fluctuations in paddy production, driven by climatic and other external factors, create uncertainty for agricultural planning and policy formulation. This study aims to model and evaluate the time-varying volatility of Maha season paddy production in the Monaragala district, Sri Lanka, using ARCH-GARCH time-series models. Annual paddy production data covering the period from 1960 to 2024 were analyzed. An Autoregressive (AR) model was first fitted to capture the conditional mean, while the Augmented Dickey–Fuller (ADF) test was used to assess stationarity. The presence of conditional heteroskedasticity was examined using the ARCH-LM test before estimating ARCH and GARCH volatility models. The ADF test confirmed that the log-return series was stationary ($p < 0.001$), while the ARCH-LM test indicated significant ARCH effects ($p < 0.05$), supporting the use of volatility models. Model estimation showed that the AR (1)-ARCH (1) model adequately captured the short-term volatility dynamics of Maha season paddy production. Although the unconstrained GARCH (1, 1) model produced statistically significant coefficients, it violated the non-negativity condition of conditional variance due to a negative ARCH parameter and was therefore rejected. Consequently, the ARCH (1) model was identified as the most appropriate specification for modelling production volatility. The findings provide useful insights for agricultural risk management, production forecasting, and the design of climate-resilient agricultural policies in Sri Lanka.

Keywords: ARCH-GARCH models, Monaragala district, paddy production volatility, time series econometrics

Introduction

This chapter Introduces the research by providing the background and context of the study, highlighting the research problem, and presenting the objectives of the research. It also discusses the significance of the study and reviews the relevant literature to establish the theoretical and empirical foundation of the research.

Background of the Study

In Sri Lanka, rice production is organized around two main cultivation seasons: the primary season from September to March, called the Maha season, which depends on the northeast monsoon; and the secondary season from May to August, known as the Yala season, which relies more on the southwest monsoon and irrigation [2]. This study specifically focuses on the Maha season due to its greater contribution to national paddy production and its significance in ensuring food security.

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The Monaragala district, located in the Uva Province, is a major agricultural region situated within Sri Lanka's dry and intermediate climatic zones. As such, its agricultural output is highly susceptible to variations in weather patterns, particularly rainfall [5]. Although it is a major contributor to national production, its paddy sector reflects the challenges faced by farmers in climate-sensitive regions, where unpredictable fluctuations in annual output create a cascade of economic and social problems, affecting farmer income, regional food supply, and the stability of related industries.

Research Problem

The main problem addressed by this research is the inherent volatility and unpredictability of paddy production. Traditional forecasting methods often focus on predicting production levels but fail to adequately capture and forecast production variance, or volatility. This volatility, characterized by periods of extreme and unexpected fluctuations in output, is a critical variable for risk management [10]. A year of bumper harvest followed by a year of crop failure carries different policy implications than a steady and predictable output, even if the long-term average remains the same. For a district like Monaragala, which is particularly vulnerable to climatic shocks such as droughts and floods, understanding the nature of these production shocks is paramount [2].

Research Questions

1. Is the Maha season paddy production series in the Monaragala district characterized by time varying volatility?
2. Does the Maha season paddy production series exhibit ARCH effects?
3. Which volatility model best represents the dynamics of Maha season paddy production: ARCH or GARCH?
4. What are the implications of the identified volatility patterns for agricultural risk management?

Research Objectives

The primary objective of this study is to model and forecast the volatility of paddy production in the Monaragala district for the Maha season. , Several specific objectives are formulated to achieve this objective: to analyze the historical trends and statistical properties of paddy production(Maha Season) in the Monaragala district from 1984 to 2024; to establish a suitable time series approach for modeling the mean of the paddy production growth rate; to formally test for the presence of Autoregressive Conditional Heteroskedasticity (ARCH effects) in the production data, thereby justifying the use of a volatility model; to estimate an ARCH/GARCH model to capture the time-varying volatility of paddy production for the Maha season; and to interpret the model results and discuss their implications for agricultural policy and risk management in the region.

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.

Literature Review

A literature review serves to situate the current study within the existing body of scholarly work by 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 study aims to address.

Time series analysis provides a robust framework for understanding and forecasting data collected over time [1]. For many economic and agricultural time series, a common assumption of classical regression is that the variance of the error term remains constant, or homoscedastic. In practice, however, this assumption is often violated. Most financial and economic time series exhibit periods of high volatility followed by periods of relative stability, a phenomenon known as volatility clustering [4]. , In 1982, Robert F. Engle proposed the Autoregressive Conditional Heteroskedasticity (ARCH) model [8] in his seminal paper to address this issue. This represented a groundbreaking advancement, as it treated variance as conditional and time-varying. The fundamental concept of the ARCH model is that the variance of the error term at a given time depends on the magnitude of error terms from previous periods [8]. Specifically, the ARCH (q) model defines the conditional variance as a linear function of the past q squared error terms. This enables the model to capture the tendency for large shocks (whether positive or negative) to be followed by other large shocks, and for small shocks to be followed by small shocks.

ARCH/GARCH models have been extensively applied to the price volatility of agricultural commodities and have since been extended to examine other forms of volatility. For example, [10] found that GARCH models were highly effective in forecasting volatile agricultural prices in India compared to simpler models such as ARIMA, indicating that agricultural markets can exhibit strong erratic behavior [10].

Closer to the focus of the present study, these models have also been applied to crop yield volatility. The GARCH models used in [11] to predict wheat yield volatility in a semi-arid region were found to be effective in forecasting yield uncertainty in a climatic zone comparable to the dry zone of Sri Lanka [11]. In their study, they demonstrated that GARCH-type models can effectively capture uncertainty in crop production arising from environmental variability.

Similarly, nonlinear time series models have been applied to model the complex production patterns of oil palm in India, further supporting the idea that simple linear models are not always sufficient for agricultural data [13]. In this context, extensions of the ARCH framework, particularly the Generalized ARCH (GARCH) model introduced by Tim Bollerslev, have become widely used for capturing more persistent volatility structures in time series data.

Time series analysis has been an agricultural forecasting tool in Sri Lanka. The ARIMA models were used [6] to predict paddy production in another big paddy-producing region in the dry zone, the Anuradhapura District, which would provide a solid methodological precedent to the current study [6]. On the same note, the ARIMA models have also been employed to forecast the prices of other agricultural products like vegetables in Sri Lanka.

Nevertheless, much of the literature recognizes that production of paddy in Sri Lanka is intensely affected by instigating factors, the most prominent of them being climate. The article by [2] examined the effects of climate change on paddy production, and the direct effects of temperature and precipitation on paddy yield [2]. Studies on the dry zone, in which Monaragala is situated, focus on the water shortages and reliance on monsoon rains, which are the key contributors to production shocks [5]. In spite of this body of work, there is an evident gap in research. Although ARIMA models have also been applied to predict the level of production, the use of ARCH/GARCH models specifically to measure and predict the volatility of paddy production at a district level in Sri Lanka is not well documented. The purpose of this paper is to close that gap by modelling the risk and uncertainty of paddy production explicitly in this critical district through the ARCH/GARCH framework.

Methodology

This section describes the data sources, preparation procedures, and econometric techniques employed to analyze the volatility of Maha season paddy production in the Monaragala district, Sri Lanka. The analysis begins with data preparation and transformation, followed by stationarity testing and the specification of the conditional mean and variance equations. The ARCH/GARCH modelling framework is then applied to capture and evaluate time-varying volatility in annual paddy production growth rates.

Data Source and Preparation

The study utilizes secondary time-series data for annual Maha season paddy production in the Monaragala district, Sri Lanka, covering the period from 1960 to 2024. The data were obtained from the Department of Census and Statistics. Production figures are measured in thousands of metric tons ('000 MT). The Monaragala district was selected because it is one of Sri Lanka's major paddy-producing districts and is highly vulnerable to climatic variability, making it an appropriate case study for modelling production volatility.

Some missing values were identified in the Maha season dataset. To maintain a continuous time series required for Autoregressive Conditional Heteroskedasticity (ARCH) modelling, linear interpolation was employed to estimate the missing values based on the preceding and succeeding years.

To analyze production volatility, the raw annual production series (p_t) was transformed into a log-return series (r_t) using the following formula:

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

This transformation produces a stationary series representing the growth rate of production. The analysis was carried out using E Views 10.

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:

$$r_t = \mu + \epsilon_t \tag{2}$$

where:

r_t is the log-return of paddy production at time t

μ represents the constant mean growth rate.

ϵ_t is the error term, representing the unexpected production shock or "innovation" for that year.

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.

$$\boldsymbol{r_t = \mu + \emptyset_1 r_{t-1} + \epsilon_t} \tag{3}$$

where,

r_t: Log returns of paddy production at time t.

μ **:** Constant baseline mean growth rate

$\boldsymbol{\emptyset_1}$: First-order autoregressive parameter

ϵ_t: Production Shock

The residuals (ϵ_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).

Conditional Variance Equation

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.

$$\sigma_t{}^2 = \omega + \alpha\epsilon_{t-1}{}^2 + \beta\sigma_{t-1}{}^2 \tag{4}$$

where,
$\sigma_t{}^2$: Conditional variance of paddy production at time t.
ω : Long-term baseline variance constant
α : ARCH parameter
β : GARCH parameter

Results and Discussion

This section presents the empirical results of the time series analysis for the paddy production of the Maha season in the Monaragala district.

Stationarity and ARCH Effect Test

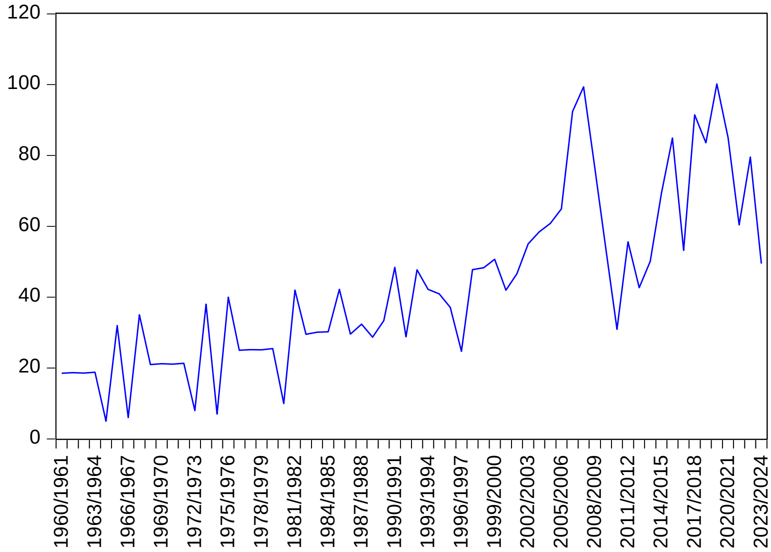

Figure 1: Time Series plot of paddy production ('000 MT) in Maha season

Figure 1 illustrates the time-series plot of Maha season paddy production in the Monaragala district from 1984 to 2024**.** The series demonstrates a noticeable long-term upward trend throughout the study period, with intermittent peaks indicating possible cyclical variations in production. The observed trend and changing variance over time suggest that the original production series is non-stationary. To statistically confirm the stationarity properties of the raw Maha season paddy production data, the Augmented Dickey–Fuller (ADF) test was performed.

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 Augmented Dickey–Fuller (ADF) test for the Maha season paddy production series in the Monaragala district. The results indicate that the series is non-stationary, with a p-value of 0.3914, which is greater than the 5% significance level. Therefore, the null hypothesis of the presence of a unit root cannot be rejected. To address the non-stationarity of the paddy production series, the original data were transformed into a log-return series (r_maha). The ADF test was then performed on the transformed series to assess its stationarity.

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 Augmented Dickey–Fuller (ADF) test for the Maha season log-return series. The results confirm that the transformed series is stationary, with a highly significant p-value of < 0.001, leading to the rejection of the null hypothesis of a unit root. The correlogram of the log-return series was then examined to determine the appropriate structure for the conditional mean equation. Based on the statistical significance of the autoregressive parameter (p-value < 0.001) and the Akaike Information Criterion (AIC) value of 1.293078, an AR(1) model was selected. Higher-order autoregressive and moving average terms were found to be statistically insignificant and were therefore excluded from the model.After filtering the conditional mean using the AR(1) process, an ARCH Lagrange Multiplier (ARCH-LM) test was performed at lag 1 to examine the presence of conditional heteroskedasticity (volatility clustering) in the residuals.

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 shows that the ARCH-LM test output and It confirms the F-statistic p-value (0.0483) and obs*R-squared p-value (0.0474) are below the 0.05 threshold, the null hypothesis of no ARCH effects is rejected at the 5% significance level. This evidence confirms the presence of time-varying volatility clustering in the Maha season paddy production residuals.

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 shows that the outputs of AR (1)-ARCH (1) model. In the conditional mean equation AR (1) parameter and in the conditional variance equation the baseline volatility constant (ω) are highly significant (both p values <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).

The significance of the ARCH parameter indicates that production volatility is influenced by short-term shocks. This finding agrees with Soliman et al. (2023), who reported that volatility models effectively capture agricultural production uncertainty under climatic variability. Similarly, Rajendran et al. (2025) highlighted the usefulness of ARCH-type models for modelling volatility in agricultural time series. Differences between the present study and previous studies may arise from differences in climatic conditions, crop type, and temporal coverage.

GARCH Model Estimation

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 displays the estimation results of the unconstrained AR (1)-GARCH (1, 1) model for the paddy production log-returns series. While the unconstrained GARCH (1, 1) model yields a highly significant p-value for the GARCH (-1) parameter (β=1.1483, p = 0.0000), this statistical significance is structurally invalid. Because the ARCH parameter (α) collapses into a negative coefficient (-0.1533, p = 0.0473), the model violates the fundamental non-negativity constraints of conditional heteroskedasticity theory. Therefore, there is no requirement to analyze or consider the summation of the ARCH and GARCH coefficients the presence of a negative variance parameter alone is sufficient to immediately disqualify the unconstrained GARCH (1, 1) model from practical consideration.

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 ($\boldsymbol{\phi}$)	-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 $\boldsymbol{R^2}$	0.5402	0.5101

Table 6 shows that the comparison of the AR (1)-ARCH (1) model and AR (1)-GARCH (1, 1). Because the GARCH estimation failed to fulfill the core theoretical boundaries of time-series econometrics by resulting in an impossible negative ARCH coefficient (α = -0.1533), the unconstrained model is structurally invalid. There is no theoretical basis to evaluate its joint parameters or variance summation, as the maximum likelihood optimization occurred across an invalid mathematical space. Consequently, the unconstrained GARCH (1, 1) framework is discarded entirely, and the AR (1)-ARCH (1) model is accepted as the true optimal framework for the Maha season.

Conclusion

This study successfully modelled the time-varying volatility and production dynamics of Maha season paddy yields in the Monaragala district from 1960 to 2024 using an autoregressive conditional heteroskedasticity framework. The findings provide important insights into the seasonal risk structure of paddy production and demonstrate the presence of volatility in annual production growth. The results indicate that the log returns of Maha season paddy production exhibit self-correcting, mean-reverting behavior, suggesting that production shocks are temporary rather than permanent. The AR(1)-ARCH(1) model was identified as the most appropriate specification, indicating that production volatility is primarily influenced by short-term shocks. Approximately 24.5% of a production shock is transmitted to the following year before dissipating relatively quickly. These findings suggest that short-term climate variability plays a significant role in influencing Maha season paddy production. Therefore, implementing short-term crop insurance schemes, together with timely climate risk management and adaptive agricultural practices, could help reduce the adverse effects of unexpected production shocks and enhance the resilience of farmers in the Monaragala district.

Limitations

The analysis is based on a univariate model, it does not include exogenous variables known to affect production, such as rainfall, temperature, fertilizer prices, or government subsidy policies. The use of annual data may also mask important intra-seasonal dynamics. In addition, this study focuses only on Maha season paddy production, and the analysis could be extended to include the Yala season for a more comprehensive understanding. Future research could build on this work in several directions. In particular, the development of a GARCH-X model, which incorporates exogenous variables such as rainfall directly into the variance equation, could provide a more nuanced explanation of the factors driving production volatility.

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