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Does Temperature and Rainfall Asymmetrically affect Wheat Production in Nepal? Using NARDL Model Approach

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Abstract

Wheat production in Nepal is highly sensitive to climatic variability, particularly temperature and rainfall. This study examines the asymmetric impacts of these climatic factors on wheat yields using the Nonlinear Autoregressive Distributed Lag (NARDL) model. A quantitative research design was employed, analyzing time-series data from 1990 to 2022. The NARDL model was used to capture both short- and long-term asymmetric effects of temperature and rainfall on wheat yield. Diagnostic and stability tests ensured the robustness of the model. The findings reveal that positive temperature changes significantly reduce wheat yields in the short term (coefficient: -2483.80, p < 0.01), followed by a compensatory positive effect in subsequent periods (coefficient: 2935.31, p < 0.01). Negative temperature changes and rainfall variability, both positive and negative, were statistically insignificant in their impacts. The model's R-squared value of 0.972 highlights its strong explanatory power. The results underscore the critical role of temperature in influencing wheat productivity, with rainfall's limited impact suggesting effective water management practices. These findings align with global studies on climate resilience but highlight unique adaptation mechanisms in Nepal. This study emphasizes the need for heat-tolerant wheat varieties and enhanced irrigation systems to mitigate climatic stressors. The use of the NARDL model offers novel insights into the asymmetric dynamics of climatic factors, advancing methodologies in climate-agriculture research.

Keywords: *Adaptive strategies, climate variability, impact agriculture, NARDL model, Nepal rainfall, temperature asymmetry, wheat production*

JEL Classification: Q54, C32, Q10

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Introduction

Wheat (Triticum aestivum L.) serves as a cornerstone of global food security, with its production highly sensitive to climatic conditions. Fluctuations in temperature and rainfall patterns have emerged as critical factors affecting wheat yields, presenting significant challenges to agricultural systems worldwide (Le Gouis et al., 2020). In Nepal, wheat is not only a staple food but also a key source of livelihood for rural communities, particularly in regions like the Terai, where its cultivation is critical to both household and national food security. However, the region is increasingly vulnerable to climate-induced stresses, including rising temperatures and erratic rainfall patterns, which have disrupted traditional farming practices and impacted yields (Devkota & Phuyal, 2015). Similar patterns are observed globally, where climate variability affects cereal crop productivity, underscoring the need for adaptive strategies tailored to local contexts (Abdi et al., 2023).

The interaction between climatic stressors and agricultural systems necessitates a multifaceted approach to understanding wheat productivity. Studies in Bhairahawa have highlighted the adverse effects of erratic rainfall and rising temperatures on wheat yields, particularly during critical growth phases (Nayava et al., 2009). These climatic disruptions have forced farmers to reconsider traditional sowing patterns, as delayed or premature sowing often leads to suboptimal yields (Thapa et al., 2020). Evidence from other regions, such as the Northern Indo-Gangetic Basin, supports the importance of early sowing as a potential mitigation strategy, emphasizing the need for location-specific interventions (Paudel et al., 2023). Moreover, the socioeconomic and technological factors influencing wheat farming cannot be overlooked, as resource constraints and limited access to modern technologies further exacerbate the challenges posed by climate variability (Kafle & Joshi, 2024; Dawadi et al., 2023).

In mountainous areas such as Lamjung District, fluctuating weather conditions present unique challenges, directly affecting wheat yields. Studies have demonstrated that combining modern agricultural technologies with climate-smart practices can mitigate some of these impacts (Poudel & Shaw, 2016; Acharya, 2018). Globally, research highlights similar challenges, with findings from East Africa and Turkey showing how climatic variability intersects with technological and socioeconomic factors to shape agricultural outcomes (Abdi et al., 2023; Karahasan & Pinar, 2023). These insights reinforce the importance of integrating scientific innovations with traditional knowledge to address region-specific challenges effectively.

Adaptation strategies, such as the adoption of climate-smart agricultural practices, are increasingly recognized as vital for mitigating climatic stressors. For instance, research in Nepal’s Koshi River Basin has demonstrated the dual impact of farming practices and climatic factors on wheat yields, emphasizing the potential of interventions like crop simulation models to inform strategic planning (Dahal et al., 2021; Amgain et al., 2024). In addition, studies using econometric models in China, India, and Iran provide valuable comparative insights, illustrating how advanced tools can capture the asymmetric and nonlinear impacts of climate variability on wheat production (Mujtaba et al., 2023; Chandio et al., 2021; Pakrooh & Kamal, 2023).

This study seeks to examine the asymmetric impacts of temperature and rainfall on wheat production in Nepal using the Nonlinear Autoregressive Distributed Lag (NARDL) model. By analyzing time-series data, this approach captures both short- and long-term dynamics, offering a nuanced understanding of the interactions between climatic variables and wheat yields. The findings aim to inform evidence-based policy decisions and adaptive agricultural strategies, ensuring the resilience of

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wheat production systems amidst growing climatic uncertainties. Insights from this research will contribute to the broader global discourse on climate change and agricultural sustainability, aligning with similar studies that emphasize balancing food security with environmental resilience (Han et al., 2023; Yanagi, 2024).

Literature Review

Climate Change and Wheat Yield

Climate change significantly influences wheat production globally, with temperature and precipitation identified as critical factors. Research in Western Europe indicates that changes in agricultural practices and climate have jointly shaped wheat yields, highlighting the need for adaptation strategies to maintain productivity (Le Gouis et al., 2020). In Nepal, the Terai region—a major wheat-producing area—has already experienced adverse climatic impacts. Studies reveal that rising temperatures and erratic rainfall patterns have led to yield fluctuations, emphasizing the vulnerability of wheat production in the region (Devkota & Phuyal, 2015). These findings align with studies in East Africa, which demonstrate that climatic variability significantly affects cereal crop productivity, necessitating location-specific adaptive measures (Abdi et al., 2023).

Climatic Stressors and Sowing Patterns

Temperature and rainfall fluctuations are key climatic stressors affecting wheat yields. Research in Bhairahawa, Nepal, underscores the significant impact of erratic rainfall and rising temperatures on wheat production, particularly during critical growth periods (Nayava et al., 2009). These climatic stressors have disrupted traditional sowing patterns, with delayed or early sowing causing suboptimal yields (Thapa et al., 2020). Furthermore, studies from the Northern Indo-Gangetic Basin suggest that early sowing could mitigate some of these impacts, underscoring the importance of adaptive agronomic practices (Paudel et al., 2023). Evidence from West Nawalparasi, Nepal, further highlights the importance of adjusting sowing patterns and adopting improved varieties to enhance resilience and productivity (Dawadi et al., 2023).

Technological and Socioeconomic Factors

Beyond climate, technological and socioeconomic factors also play a crucial role in wheat production. In the Kanchanpur district of Nepal, the adoption of modern agricultural technologies has been identified as a potential solution to address productivity gaps and production limitations (Kafle & Joshi, 2024). However, barriers such as limited access to resources and infrastructure constrain widespread adoption. Studies from mountainous regions like Lamjung further highlight the combined effects of climate variability and inadequate technological interventions, which exacerbate yield instability (Poudel & Shaw, 2016; Acharya, 2018). Research from long-term field trials in Europe corroborates these findings, showing that mineral fertilization and weather variability interact to significantly influence grain yield and stability (Hlisnikovský et al., 2023).

Climate-Smart Agricultural Practices

Adopting climate-smart agricultural practices has shown promise in mitigating the impacts of climatic stressors on wheat production. Research in the Koshi River Basin emphasizes the dual role of climatic and farming practices in influencing wheat yields, highlighting the potential of climate-smart interventions (Dahal et al., 2021; Gairhe et al., 2021). Crop simulation models from the Western Terai

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provide predictive insights into wheat yield trends under various climatic scenarios, offering valuable guidance for strategic planning (Amgain et al., 2024; Devkota et al., 2024). Similarly, econometric models from Iran have highlighted the potential for modeling climatic and socioeconomic factors to inform policy interventions (Pakrooh & Kamal, 2023). In addition, evidence from North China underscores the importance of balancing agricultural production with environmental sustainability to enhance resilience in wheat production systems (Shi & Umair, 2024).

Global Perspectives and Comparative Insights

Globally, studies have documented the diverse impacts of climate change on wheat yields. Research from China and India highlights the interplay of climatic and technological factors, illustrating the need for balanced approaches to sustain production while addressing environmental concerns (Chandio et al., 2023a; Mujtaba et al., 2023). Similarly, investigations in semi-arid regions using advanced modeling techniques demonstrate how projected climatic scenarios could shape wheat crop suitability (Alsafadi et al., 2023). Econometric analyses from Turkey and East Africa reveal that regional variability in climatic impacts often depends on localized factors such as soil quality, infrastructure, and access to technology (Karahasan & Pinar, 2023; Abdi et al., 2023). These global insights resonate with findings from Nepal, where the integration of climate-resilient practices and advanced technologies could bridge productivity gaps and ensure sustainable wheat production in the face of growing climatic uncertainties.

This body of literature highlights the intricate relationships between climate change, technological factors, and wheat production, providing a foundation for evidence-based policy development and adaptive strategies to sustain agricultural productivity in Nepal.

Research Gap

Despite extensive research on the impacts of climate change on wheat production, gaps remain in understanding the specific effects of temperature and rainfall on wheat yields in Nepal, particularly across diverse agro-ecological zones. Studies highlight climatic variability's role in wheat production in the Terai and mountainous regions (Devkota & Phuyal, 2015; Poudel & Shaw, 2016). However, the dynamic, long-term nonlinear interactions of climatic variables with wheat yields using advanced econometric approaches, like the NARDL model, remain underexplored.

Adaptive practices such as early sowing and technological interventions have been suggested (Thapa et al., 2020; Paudel et al., 2023), but these studies often lack integration of climatic data with production trends to account for asymmetries in short- and long-term impacts. Neighboring regions like India and China have utilized econometric frameworks to analyze these relationships (Chandio et al., 2023a; Mujtaba et al., 2023), providing a basis for similar analyses in Nepal. Additionally, socio-economic barriers to adopting climate-resilient practices, particularly in resource-constrained regions like Kanchanpur, require further empirical investigation (Kafle & Joshi, 2024; Bist et al., 2017).

This study addresses these gaps by employing the NARDL model to analyze asymmetric impacts of temperature and rainfall on wheat production in Nepal. By capturing both short- and long-term dynamics, this research aims to inform evidence-based policymaking and develop climate-resilient agricultural strategies tailored to Nepal's diverse agro-climatic contexts.

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Research Methods

Research Design

This study employs a quantitative research design to analyze the relationship between temperature, rainfall, and wheat yield in Nepal. Using time-series data from 1990 to 2022, the research identifies both short-term and long-term impacts of climatic variables on wheat production. The Nonlinear Autoregressive Distributed Lag (NARDL) model is utilized to capture the dynamic and asymmetric interactions between these variables, making it particularly suitable for analyzing non-stationary data with mixed integration orders and exploring nonlinear relationships.

Data Sources

The study relies on secondary data collected from reputable databases. Wheat yield data were obtained from the Food and Agriculture Organization (FAO, 2024), while climate data, including temperature and rainfall, were sourced from the Climate Change Knowledge Portal (CCKP, 2024). These datasets provide comprehensive and reliable information necessary for the analysis of climatic impacts on wheat production.

Variables

The key variables examined in this study include:

Wheat Yield (dependent variable): Measured annually in kilograms per hectare, representing the productivity of wheat cultivation.

Temperature (independent variable): Annual average temperature in degrees Celsius, reflecting the thermal conditions affecting wheat growth.

Rainfall (independent variable): Annual cumulative rainfall in millimeters, indicating water availability critical for wheat production.

Data Analysis Methodology

The NARDL model is employed to analyze the asymmetric relationship between wheat yield and the climatic variables of temperature and rainfall. This model is particularly advantageous for time-series data that may exhibit non-stationarity, mixed levels of integration (I(0) and I(1)), and nonlinear dynamics. The analysis involves the following steps:

Stationarity Testing: Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are applied to examine the stationarity of each variable.

Lag Selection: Optimal lag lengths are determined using criteria such as the Akaike Information Criterion (AIC) and Schwarz Criterion (SC).

NARDL Estimation: The model estimates short-term and long-term relationships while capturing potential nonlinear and asymmetric effects of the independent variables on wheat yield.

Model Specification

The ARDL model is specified as follows:

$$Y_t = \beta_0 + \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{j=0}^{q} \alpha_j^+ [X(t-j)^+ + \alpha_j^- X(t-j)^-] + \epsilon_t \text{ ....} (1)$$

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Where,

Y_t is the dependent variable (Wheat Yield) at time t,

X_{t-j}^{+} and X_{t-j}^{-} represent positive and negative changes in the independent variables (Temperature and Rainfall), respectively.

β_0 is the constant term,

β_i and α_j^{+} , α_j^{-} are coefficients for the lagged dependent and independent variables, respectively,

ϵ_t is the error term,

p and q denote the lag lengths for the dependent and independent variables, respectively.

Bounds Testing: A bounds test is conducted to determine whether a cointegrating relationship exists between the variables.

Diagnostic Testing: Post-estimation diagnostics, including tests for autocorrelation, heteroskedasticity, normality, and parameter stability, are performed to validate the model.

Software and Tools: The analysis is conducted using statistical software E-views version 12, which provide robust tools for time-series econometric modeling. Visualization tools are used to depict trends and relationships among the variables over the study period.

Limitations

While the study provides valuable insights, it is limited by the availability of secondary data, which may not fully capture localized variations in climatic impacts. Future research could incorporate additional variables, such as soil quality and technological inputs, to enhance the robustness of the analysis.

By applying this rigorous methodology and leveraging the NARDL model, the study aims to uncover the complex and asymmetric interactions between temperature, rainfall, and wheat yield. These findings will contribute to evidence-based policymaking and the development of climate-resilient agricultural strategies for Nepal.

Data Analysis and Results

Trends in Key Variables for the Analysis

The trends in wheat yield, temperature, and rainfall from 1990 to 2022 reveal significant variability, underscoring the influence of climatic fluctuations on agricultural productivity. While wheat yields have shown an upward trajectory with periodic dips, temperature and rainfall patterns exhibit inconsistencies, reflecting potential challenges in maintaining sustainable production amidst climate variability.

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Figure 1: Trends in Wheat Yield, Temperature and Rainfall (1990-2022)

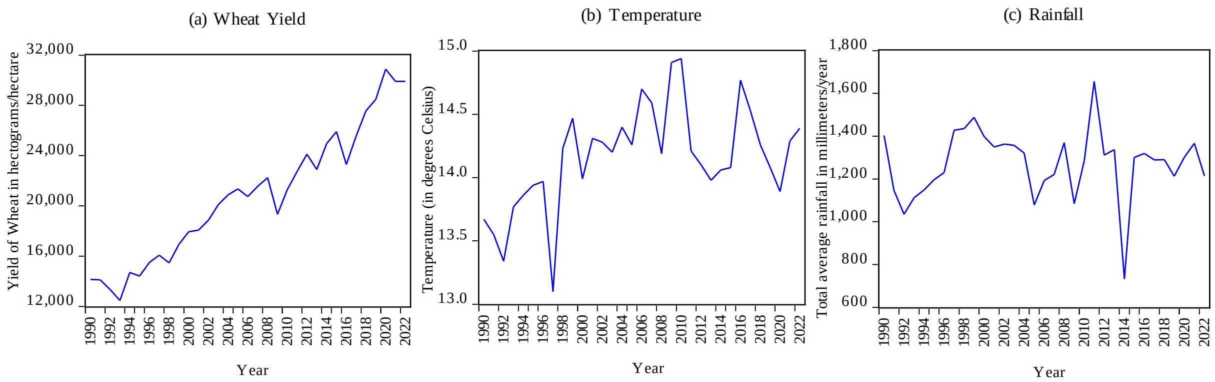

Figure 1(a) depicts the temporal progression of wheat yield in Nepal over the 1990–2022 period. The graph shows a generally upward trajectory, reflecting advancements in agricultural techniques, policy interventions, and possible adaptations to changing climatic conditions. However, intermittent declines in yield suggest periods of stress, possibly due to unfavorable climatic conditions, inadequate technological inputs, or socio-economic constraints. These fluctuations underscore the sensitivity of wheat production to external factors and the need for resilience-building measures in agricultural systems. Figure 1(b) highlights the rising trend in average annual temperature over the same period. The gradual increase aligns with global climate change trends, signifying potential risks such as thermal stress on wheat crops, particularly during critical growth phases. The data also hint at the necessity for targeted mitigation strategies, such as heat-resistant crop varieties or adjustments in sowing dates, to cope with this warming trend and minimize its adverse effects on wheat productivity. Figure 1(c) illustrates the variability in annual rainfall during the 1990–2022 timeframe. The data reveal no clear trend, but instead highlight significant inter-annual fluctuations. Such erratic rainfall patterns can lead to water stress or excess moisture conditions, both of which adversely affect wheat growth. The analysis points to the critical role of efficient water management systems and adaptive strategies to mitigate the impacts of rainfall variability on wheat production.

Descriptive Statistics

The descriptive statistics summarize the central tendency, dispersion, and shape of the distribution for wheat yield, temperature, and rainfall over 33 observations. Key metrics, including mean, standard deviation, and skewness, reveal significant variability in rainfall and wheat yield, highlighting potential influences on agricultural outcomes.

Table 1: Descriptive Statistics of Key Variables

	Wheat Yield	**Temperature**	**Rainfall**
Mean	20780.58	14.16	1271.93
Median	20873.00	14.20	1300.03
Maximum	30887.00	14.94	1656.02
Minimum	12460.00	13.10	732.86
Std. Dev.	5230.73	0.41	161.20
Skewness	0.25	-0.35	-0.83
Kurtosis	2.11	3.39	5.62
Observations	33	33	33

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Table 1 provides a statistical summary of the three key variables analyzed in the study: wheat yield, temperature, and rainfall. The mean wheat yield is 20,780.58 kg/ha, indicating the average productivity level over 33 observations, with a standard deviation of 5,230.73 kg/ha, which reflects substantial variability in yield across the years. The positive skewness (0.25) suggests a slight right-tailed distribution, implying that higher-than-average yields occurred more frequently than lower ones.

Temperature exhibits a relatively narrow range, with a mean of 14.16°C and a standard deviation of 0.41°C, signaling moderate year-to-year fluctuations. Its negative skewness (-0.35) indicates a slightly higher frequency of below-average temperature values.

Rainfall, critical for wheat production, shows the most significant variability, with a mean of 1,271.93 mm and a standard deviation of 161.20 mm. The negative skewness (-0.83) and high kurtosis (5.62) suggest occasional years of unusually low rainfall, which could have posed challenges to crop growth. These statistics highlight the importance of addressing climatic variability and its asymmetric impacts on wheat production through adaptive measures and informed policy decisions.

Table 2: Correlation Analysis

	Wheat Yield	**Temperature**	**Rainfall**
Wheat Yield	1		
Temperature	0.39	1	
Rainfall	0.04	0.07	1

Table 2 presents the correlation coefficients between wheat yield, temperature, and rainfall, providing insights into their linear relationships. Wheat yield exhibits a moderate positive correlation (0.39) with temperature, suggesting that temperature variations, within certain limits, may positively influence wheat productivity. However, extreme deviations could result in negative impacts, as indicated in other sections of the analysis.

The correlation between wheat yield and rainfall is notably weaker (0.04), indicating a minimal linear association. This could imply that rainfall's impact on wheat yield may be more complex and nonlinear, requiring advanced modeling approaches to uncover its true influence.

The weak positive correlation (0.07) between temperature and rainfall suggests minimal direct interdependence between these climatic variables during the study period. These findings underscore the necessity for a nonlinear approach, such as the NARDL model, to capture asymmetric and dynamic interactions between these variables and wheat production.

Unit Root Testing

The unit root testing results confirm the mixed stationarity of the variables, with some achieving stationarity at level and others at first difference. This justifies the use of the NARDL model, which accommodates variables integrated at I(0) and I(1)(Khatri et al., 2025).

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Table 3: Unit Root Test Results

		Phillips-Perron (PP)		
At Level	**Statistic**	**Wheat Yield**	**Temperature**	**Rainfall**
With Constant	t-Statistic	0.2284	-3.0719**	-4.6110***
With Constant & Trend	t-Statistic	-3.7490**	-3.5781**	-4.5575***
Without Constant & Trend	t-Statistic	3.0761	0.6691	-0.5602
At First Difference		**d(Wheat Yield)**	**d(Temperature)**	**d(Rainfall)**
With Constant	t-Statistic	-7.8820***	-10.2634***	-19.9706***
With Constant & Trend	t-Statistic	-8.5164***	-15.5025***	-19.4369***
Without Constant & Trend	t-Statistic	-6.0332***	-9.7346***	-20.3625***
		Augmented Dickey-Fuller (ADF)		
At Level		**Wheat Yield**	**Temperature**	**Rainfall**
With Constant	t-Statistic	-0.1874	-3.2174**	-4.6123***
With Constant & Trend	t-Statistic	-3.7988**	-3.6434**	-4.5552***
Without Constant & Trend	t-Statistic	1.9775	0.2347	-0.2407
At First Difference		**d(Wheat Yield)**	**d(Temperature)**	**d(Rainfall)**
With Constant	t-Statistic	-5.9197***	-6.5619***	-8.1593***
With Constant & Trend	t-Statistic	-5.9242***	-6.6609***	-7.9960***
Without Constant & Trend	t-Statistic	-6.0520***	-6.5880***	-8.2989***

Notes: (*) = 10%; (**) = 5%; and (***) = 1% Significant respectively.

Table 3 presents the results of the unit root tests, including both ADF and PP tests, conducted to examine the stationarity of wheat yield, temperature, and rainfall. At levels, temperature and rainfall demonstrate stationarity under certain conditions (e.g., with constant and trend), as indicated by significant test statistics at the 5% and 1% levels, respectively. However, wheat yield shows non-stationarity at level across all conditions.

After first differencing, all three variables—wheat yield, temperature, and rainfall—become stationary, with significant test statistics across all specifications (constant, constant & trend, and no constant & trend). This confirms that the variables are integrated of mixed orders, specifically I(0) and I(1).

The presence of mixed integration validates the choice of the Nonlinear Autoregressive Distributed Lag (NARDL) model, which can effectively handle such scenarios. This ensures robust estimation of the relationships between climatic variables and wheat yield while accounting for their dynamic and asymmetric interactions.

Lag Length Selection

The lag length selection, based on criteria like AIC and SC, identifies an optimal lag structure that balances model fit and parsimony. The chosen lags ensure the inclusion of relevant past dynamics in analyzing wheat yield and climatic variables (Poudel, 2023).

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Table 4: Criteria of Lag Length Selection

Lag	Log L	LR	FPE	AIC	SC	HQ
0	-484.6071	NA	8.07e+10	33.62807	33.76952	33.67237
1	-437.8353	80.64102*	6.00e+09	31.02312	31.58890*	31.20032*
2	-428.4672	14.21368	5.99e+09*	30.99774*	31.98785	31.30783
3	-424.3631	5.377797	8.91e+09	31.33538	32.74983	31.77837
4	-416.9451	8.185297	1.12e+10	31.44449	33.28327	32.02037

Table 4 presents the lag length selection process, a critical step in time series analysis to ensure accurate representation of dynamic relationships between variables. The selection relies on statistical criteria such as the AIC, SC, HQ, and the LR, which balance model fit and parsimony. The results indicate that a lag length of 1 is optimal, as it minimizes the AIC (30.99774) and aligns with most other criteria, ensuring the model effectively captures the necessary dynamics without overfitting. The LR statistic supports this choice by showing significant improvement at this lag. By accounting for past values of both dependent and independent variables, the selected lag structure provides a robust foundation for estimating short-term and long-term effects, particularly within the NARDL framework.

NARDL Model Result

The NARDL results reveal significant asymmetric impacts of temperature and rainfall on wheat yield in Nepal. Positive temperature changes have a pronounced effect, while the influence of rainfall variability remains statistically insignificant, emphasizing the critical role of thermal stress in wheat productivity.

Table 5: Results of NARDL Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
WHEAT_YIELD(-1)	0.585320	0.135683	4.313874	0.0002
TEMPERATURE_POS	-2483.800	708.4179	-3.506123	0.0018
TEMPERATURE_POS(-1)	2935.308	741.3819	3.959239	0.0006
TEMPERATURE_NEG	-748.0825	972.7236	-0.769060	0.4494
RAINFALL_POS	0.565250	1.390700	0.406450	0.6880
RAINFALL_NEG	-0.031185	1.109230	-0.028114	0.9778
C	5984.280	1644.913	3.638052	0.0013
R-squared	0.971997	Mean dependent var		21209.90
Adjusted R-squared	0.964996	S.D. dependent var		5103.121
S.E. of regression	954.7642	Akaike info criterion		16.75649
Sum squared resid	21877791	Schwarz criterion		17.08029
Log likelihood	-252.7255	Hannan-Quinn criter.		16.86204
F-statistic	138.8399	Durbin-Watson stat		2.011516
Prob(F-statistic)	0.000000			

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The NARDL results highlight the asymmetric effects of temperature and rainfall on wheat yield in Nepal in Table 5. The lagged dependent variable, Wheat Yield (-1), has a coefficient of 0.585, significant at the 1% level, indicating strong inertia in wheat yield dynamics, where past values significantly influence current yields. Positive temperature shocks (Temperature_Pos) show a significant negative immediate effect (-2483.80, p = 0.0018) but a positive lagged effect (2935.31, p = 0.0006), suggesting short-term stress followed by possible adaptation or compensatory growth in subsequent periods. Conversely, negative temperature changes (Temperature_Neg) are statistically insignificant, indicating limited adverse effects of cooling on wheat yield within the studied timeframe.

Rainfall variability appears to play a less pronounced role in affecting wheat yield. Both positive (Rainfall_Pos) and negative rainfall shocks (Rainfall_Neg) are statistically insignificant, with t-statistics of 0.406 and -0.028, respectively. This suggests that rainfall's impact on wheat production might be nonlinear or mitigated by irrigation and water management practices. The constant term (C), significant at the 1% level, reflects baseline productivity levels independent of climatic factors, emphasizing the role of underlying agricultural practices and technologies.

The model's diagnostics demonstrate its robustness and explanatory power. With an R-squared value of 0.972 and an adjusted R-squared of 0.965, the model explains a substantial portion of the variability in wheat yield. The F-statistic (138.84, p < 0.0001) confirms the overall significance of the model, while the Durbin-Watson statistic (2.01) indicates no significant autocorrelation in the residuals. These results underscore the importance of temperature as a critical climatic variable in wheat production and highlight the need for further exploration of rainfall's complex role in agricultural outcomes.

NARDL Long Run Form and Bounds Test

Table 6 presents the ARDL long-run coefficients and bounds test results, confirming a significant long-run relationship among the variables. The F-statistic of 6.166511 exceeds the critical bounds at all significance levels, validating cointegration (Pesaran et al., 2001).

Table 6: NARDL Bounds Test Results

Test Statistic	Value	Signif.	I(0)	I(1)
Asymptotic: n = 1000				
k	4	5%	2.56	3.49
		2.5%	2.88	3.87
		1%	3.29	4.37
Actual Sample Size 31			Finite Sample: n = 35	
		10%	2.46	3.46
		5%	2.947	4.088
		1%	4.093	5.532
Finite Sample: n = 30				
		10%	2.525	3.56
		5%	3.058	4.223
		1%	4.28	5.84

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Table 6 presents the NARDL bounds test results, confirming a long-run cointegrating relationship among wheat yield, temperature, and rainfall. The calculated F-statistic (6.166) exceeds the upper critical bounds (I(1)) at all significance levels (1%, 2.5%, 5%, and 10%), indicating that these variables maintain a stable long-term equilibrium despite short-term asymmetries and fluctuations. This validation supports the suitability of the NARDL model for capturing both dynamic short-term effects and nonlinear long-term interactions.

The presence of cointegration highlights the sustained impact of climatic variables on wheat production in Nepal. The findings emphasize the importance of formulating adaptive agricultural strategies that address long-term climatic challenges, such as developing heat-tolerant wheat varieties and improving water management practices. This insight provides a solid foundation for evidence-based policy decisions aimed at enhancing agricultural resilience and ensuring sustainable food security.

Table 7: Short Run Coefficients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
d(Temperature_Pos)	-2483.800	518.4612	-4.790716	0.0001
CointEq(-1)*	-0.414680	0.062019	-6.686345	0.0000

Table 7 presents the short-run coefficients derived from the NARDL model, capturing the immediate and asymmetric effects of temperature and rainfall changes on wheat yield. The positive temperature changes (d(Temperature_Pos)) have a significant negative impact on wheat yield in the short term, with a coefficient of -2483.80 ($p = 0.0001$). This indicates that sudden increases in temperature create immediate stress on wheat crops, potentially due to thermal stress during critical growth phases. Conversely, other variables, including rainfall changes (both positive and negative), are statistically insignificant in the short run, suggesting a limited immediate influence of rainfall variability on wheat production.

The error correction term (CointEq(-1)) is statistically significant and negative, with a coefficient of -0.4147 ($p < 0.0001$). This confirms the presence of a stable adjustment mechanism, where deviations from the long-run equilibrium are corrected at a rate of approximately 41% per period. The significance of the error correction term highlights the strong tendency of the system to revert to its long-term equilibrium, even when short-term climatic shocks occur. These findings underscore the critical need for strategies that mitigate the immediate adverse effects of temperature spikes, while the model’s stability ensures reliable predictions for long-term planning.

Long Run Coefficients

The long-run coefficients reveal that temperature changes have a more pronounced impact on wheat yield compared to rainfall, though the effects are statistically insignificant. This underscores the complex and nonlinear relationship between climatic variables and wheat production, highlighting the need for climate-resilient strategies.

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Table 8: Long Run Coefficients of Key Variables

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Temperature_Pos	1088.809	1314.909	0.828048	0.4158
Temperature_Neg	-1803.999	2131.546	-0.846334	0.4057
Rainfall_Pos	1.363098	3.461422	0.393797	0.6972
Rainfall_Neg	-0.075203	2.668866	-0.028178	0.9778
C	14431.08	1490.006	9.685250	0.0000

Table 8 presents the long-run coefficients from the NARDL model, highlighting the sustained impacts of temperature and rainfall variability on wheat production in Nepal. The coefficients for positive and negative changes in temperature (1088.809 and -1803.999, respectively) suggest potential directional impacts, but these relationships are statistically insignificant. Similarly, the coefficients for rainfall changes (positive: 1.363098; negative: -0.075203) indicate a lack of significant long-run effects, likely due to the mitigating role of irrigation systems and adaptive agricultural practices. However, the constant term (14431.08, significant at the 1% level) underscores the importance of stable baseline factors such as advanced farming techniques and technological inputs in maintaining wheat productivity despite climatic variability.

These findings imply a complex and nonlinear relationship between climatic factors and wheat yields, emphasizing the need for adaptive strategies. Policymakers should focus on promoting climate-resilient agricultural practices, such as the development of heat-tolerant wheat varieties and efficient irrigation systems, to buffer against climatic stressors. The results also highlight the critical role of technological advancements and resource optimization in enhancing long-term agricultural sustainability, ensuring stable productivity levels even in the face of climate variability. This integrated approach can provide a robust foundation for food security and economic resilience in Nepal's agricultural sector.

Stability and Diagnostics Tests

Table 10 presents the diagnostics and stability tests, confirming the model's reliability and robustness. The results indicate that the residuals are normally distributed, free from serial correlation and heteroscedasticity, and the model parameters remain stable over time.

Table 9: Diagnostics and Stability Tests

Diagnostics	Statistics	p-value
Normality(J-B)	1.62	0.44
Serial Correlation $\chi^2(2)$	0.13	0.94
B-P-G Test(Scaled explained SS)	4.74	0.58
CUSUM Test	Stable	
CUSUM of Square Test	Stable	

Table 9 provides critical diagnostic and stability test results to ensure the robustness of the NARDL model. The Jarque-Bera test confirms that the residuals are normally distributed (p = 0.44), ensuring unbiased and efficient coefficient estimates (See Figure 2). The Breusch-Godfrey LM test indicates no

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serial correlation in the residuals (p = 0.94), suggesting that the model captures all relevant dynamics without systematic errors *(See Table 11).* Additionally, the Breusch-Pagan-Godfrey test reveals constant variance in the residuals (p = 0.58), confirming homoscedasticity and reliable coefficient estimates *(See Table 12).*

Stability tests, including the CUSUM and CUSUM of Squares, validate the consistency of model parameters over time, with no significant deviations detected (See Figure 3 & Figure 4). These results confirm the robustness of the model in analyzing the long-term and short-term relationships between climatic variables and wheat production. Together, the diagnostics and stability tests demonstrate that the NARDL model is well-specified, providing a solid foundation for drawing reliable conclusions to inform adaptive agricultural strategies and policy decisions in Nepal.

Figure 2: Histogram of Residuals for Normality Test

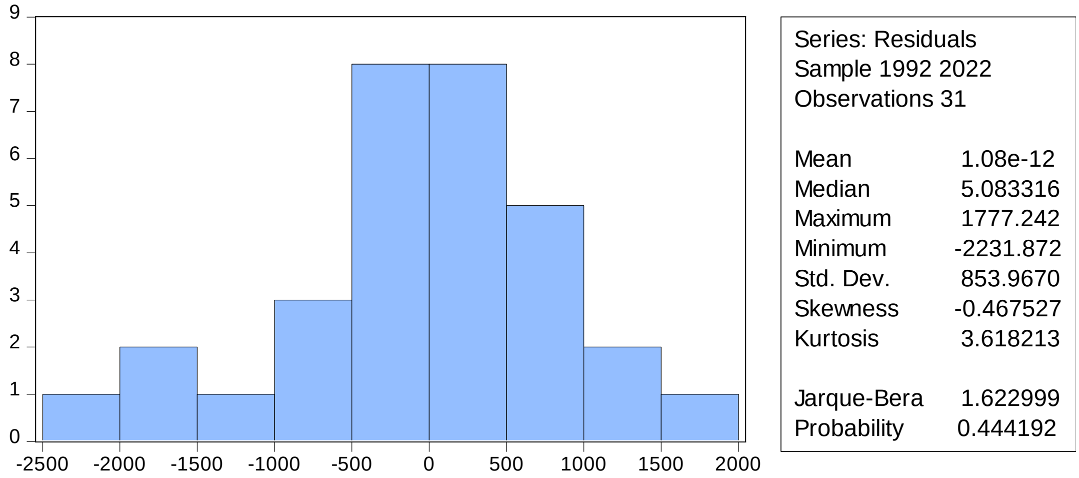

Table 10: Breusch-Godfrey Serial Correlation LM Test Results

F-statistic	0.046381	Prob. F(2,22)	0.9548
Obs*R-squared	0.130161	Prob. Chi-Square(2)	0.9370

Table 11: Heteroskedasticity Test Results Using BPG Method

F-statistic	0.967877	Prob. F(6,24)	0.4676
Obs*R-squared	6.039640	Prob. Chi-Square(6)	0.4188
Scaled explained SS	4.738983	Prob. Chi-Square(6)	0.5777

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Figure 3: CUSUM Test for Stability of Model Parameters

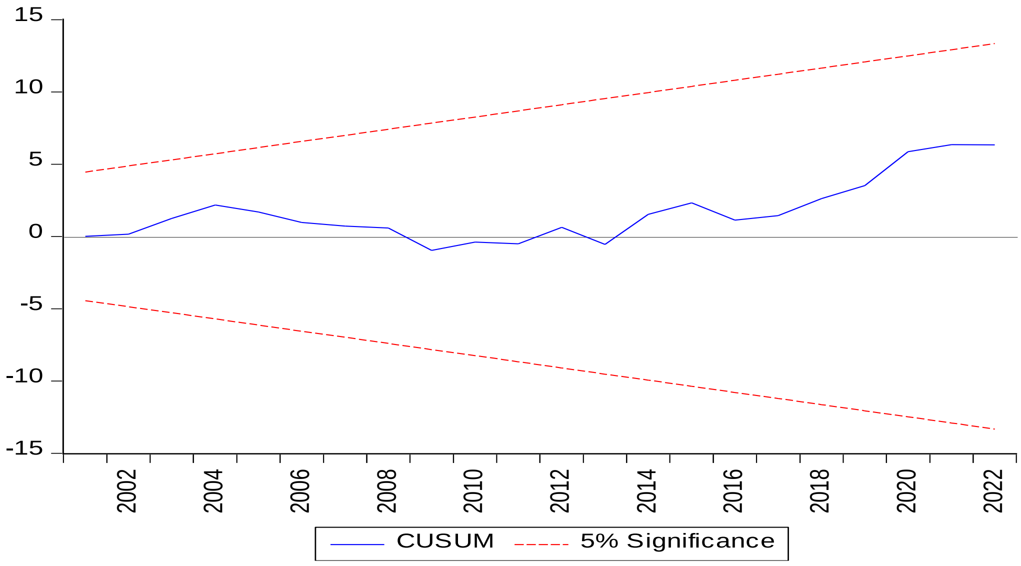

Figure 4: CUSUM of Squares Test for Stability of Model Parameters

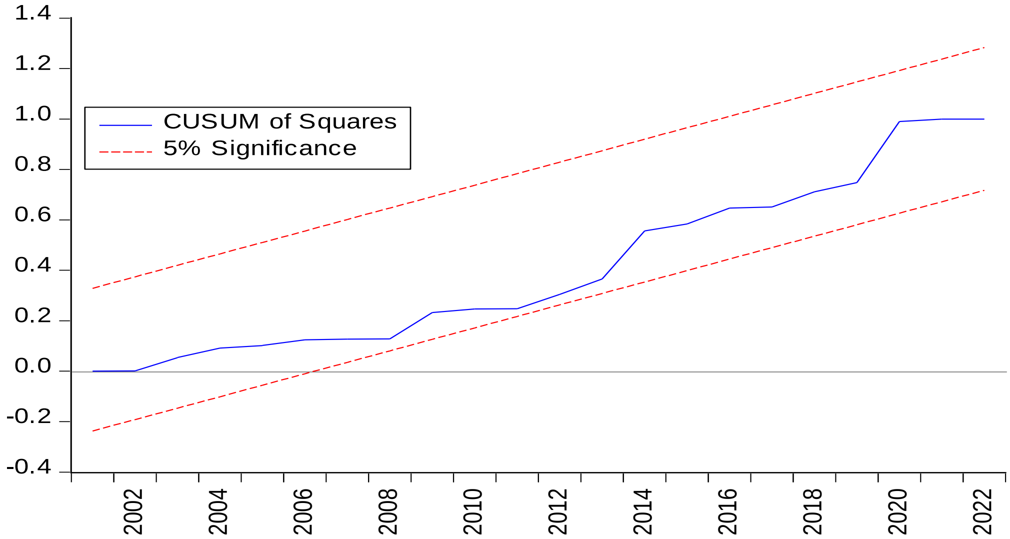

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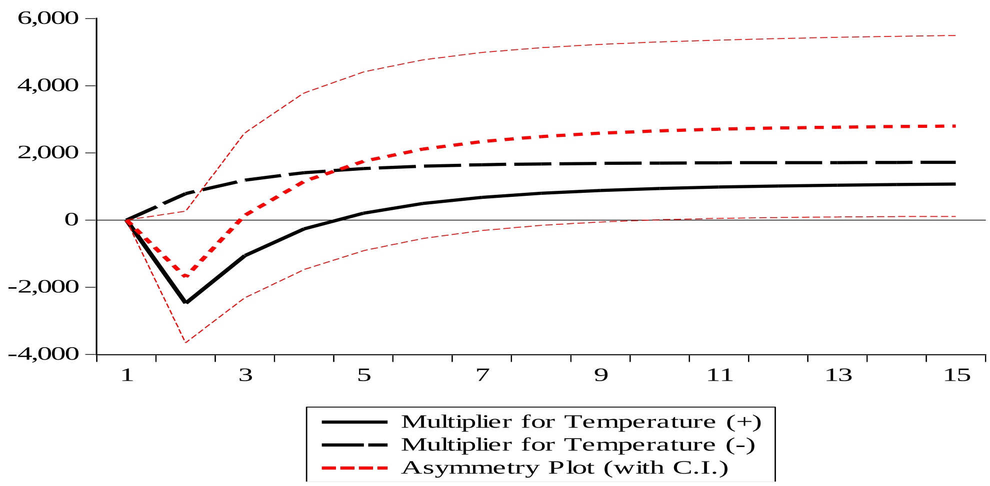
Figure 5: NARDL Multiplier Effects of positive and negative Temperature on Wheat Yield



The NARDL multiplier graph illustrates the dynamic and asymmetric responses of wheat yield to positive and negative changes in temperature. Positive temperature shocks initially reduce wheat yield due to thermal stress, but the yield gradually recovers over time, suggesting adaptation or compensatory growth. Negative temperature shocks have minimal impact, indicating less vulnerability to cooling. The graph underscores the need for targeted strategies to address short-term thermal stress to sustain wheat production in Nepal.

Figure 6: Multiplier effects of positive and negative rainfall changes on wheat yield

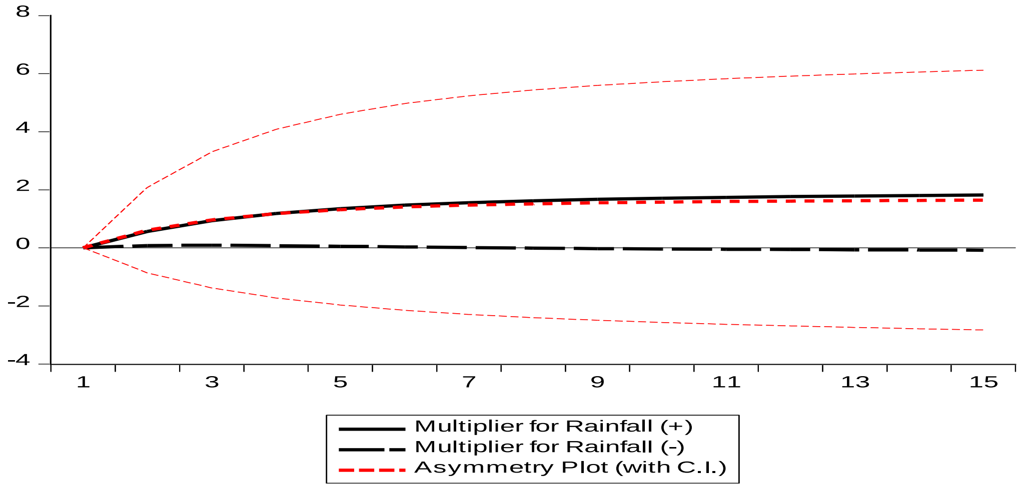


Figure 6 illustrates the multiplier effects of positive and negative rainfall changes on wheat yield, along with the asymmetry plot and confidence intervals. The solid black line shows the positive rainfall multiplier, indicating a gradual and stable benefit to wheat yield from increased rainfall, while the dashed black line represents the negative multiplier, reflecting minimal adverse impacts of reduced rainfall—likely due to effective water management practices such as irrigation. The red dashed asymmetry plot highlights the difference between positive and negative rainfall impacts, with wide confidence intervals suggesting relatively symmetric effects. This highlights the limited direct

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influence of rainfall variability on wheat yield, emphasizing the buffering role of water management in mitigating rainfall shocks.

Discussion

The findings from this study provide critical insights into the asymmetric effects of temperature and rainfall on wheat production in Nepal. Positive temperature changes exhibit a significant negative short-term impact, consistent with thermal stress observed in other studies (Chandio et al., 2023). However, the lagged positive effect suggests potential adaptation or compensatory growth mechanisms in subsequent periods, aligning with findings from studies in East Africa and North China, where crops demonstrate resilience under moderate climatic stress (Abdi et al., 2023; Shi & Umair, 2024). In contrast, negative temperature changes were statistically insignificant, suggesting that cooling periods exert limited adverse effects, a finding also corroborated by research in temperate regions like Turkey (Karahasan & Pinar, 2023).

Rainfall variability, both positive and negative, showed limited influence on wheat production in the short run. This result contrasts with studies from Iran and India, where rainfall was a critical determinant of yield variability (Pakrooh & Kamal, 2023; Mujtaba et al., 2023). The negligible impact in this study may be attributed to effective irrigation systems and water management practices in Nepal's wheat-producing regions. Long-term coefficients also revealed a lack of statistical significance for rainfall, resonating with findings from West Nawalparasi, Nepal, which emphasized non-climatic factors like soil quality and agricultural practices as primary drivers of wheat productivity (Dawadi et al., 2023).

The diagnostics and stability tests confirm the robustness of the NARDL model, ensuring reliable estimates for policy recommendations. The results underline the critical role of temperature as a key climatic factor influencing wheat yields, while the relatively muted effects of rainfall highlight the importance of adaptive infrastructure, such as irrigation. These findings align with global perspectives, emphasizing the necessity for localized, climate-resilient strategies. Studies from mountainous regions in Nepal and long-term trials in Europe suggest integrating modern agricultural technologies with traditional knowledge to address climatic challenges effectively (Poudel & Shaw, 2016; Hlisnikovský et al., 2023). Moreover, economic analyses from China and North India stress the importance of balancing productivity with environmental sustainability, reinforcing the global applicability of this study's conclusions (Chandio et al., 2023a; Shi & Umair, 2024).

In summary, the study highlights temperature as a critical factor in Nepal's wheat production, with significant implications for policy and adaptive strategies. The findings advocate for developing heat-resistant wheat varieties and enhancing water management systems to mitigate climatic stressors. By comparing these results with regional and global studies, this research underscores the need for integrating advanced econometric models with field-based practices to ensure sustainable agricultural productivity.

Conclusion

This study highlights the asymmetric impacts of temperature and rainfall on wheat production in Nepal, using the NARDL model to capture short- and long-term dynamics. Positive temperature changes significantly reduce wheat yields in the short run due to thermal stress, but subsequent periods show recovery, indicating adaptation mechanisms. Rainfall variability, however, exerts

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limited influence on wheat production, likely due to effective irrigation practices. These findings emphasize the critical role of temperature as a determinant of wheat productivity, while rainfall's impact appears buffered by adaptive agricultural infrastructure. By addressing these climatic factors, this study provides insights for enhancing the resilience of wheat production systems in Nepal. The results have important policy and practical implications for agricultural sustainability in Nepal. Policymakers should prioritize the development and dissemination of heat-tolerant wheat varieties to address temperature-induced stress. Investments in irrigation and water management infrastructure should also be bolstered to mitigate potential rainfall variability. Moreover, integrating climate-smart agricultural practices, such as early sowing and crop diversification, can enhance resilience. These interventions should be accompanied by capacity-building programs for farmers, focusing on the adoption of adaptive technologies and practices to sustain productivity amidst climatic uncertainties.

This study contributes to the existing literature by applying the NARDL model to analyze the asymmetric impacts of temperature and rainfall on wheat production in Nepal. The model's ability to capture both short- and long-term dynamics and nonlinear interactions offers a nuanced understanding of climatic effects. Unlike prior research that predominantly focuses on linear models or single climatic variables, this study provides a comprehensive analysis that accounts for asymmetries, thereby advancing the methodological framework for examining climate-agriculture relationships in diverse agro-ecological contexts. Future research could explore the integration of additional variables, such as soil quality, pest infestation, and technological inputs, to provide a more holistic understanding of factors affecting wheat production.

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