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Mathematical Analysis of the Impact of Climate Factors and Agricultural Practices on Rice Yield in Nepal: A Time Series Data Analysis

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Abstract

Rice is a staple food and a crucial element of Nepal's agrarian economy; however, its yield is significantly affected by climatic factors such as rainfall and temperature, as well as agricultural practices like pesticide use. Understanding these dynamics is essential for sustaining productivity in the face of climate change. This study employs an Autoregressive Distributed Lag (ARDL) model to analyze 33 years of time-series data (1990–2022), focusing on key variables including rice yield, temperature, rainfall, and pesticide use, all derived from secondary data sources. Diagnostic tests confirmed normality (p=0.06), absence of serial correlation (p=0.58), and homoscedasticity (p=0.68), with stability validated through CUSUM and CUSUMSQ tests. The results indicate that temperature has a significant positive long-term impact on rice yield (β=2181.48, p<0.05), suggesting that moderate warming can enhance productivity. Rainfall exerts a marginal positive effect (β=5.10, p=0.05), while pesticide use shows a strong correlation with yield (β=17.70, p<0.01). The Granger Causality Test identifies temperature (F=7.76, p<0.01) and pesticide use (F=11.25, p<0.01) as critical predictors of rice yield. These findings demonstrate that while temperature and pesticide use significantly affect rice yield, the impact of rainfall is diminished due to effective irrigation systems. Nevertheless, the heavy reliance on pesticides raises sustainability concerns, underscoring the necessity for integrated pest management and environmental safeguards. This study advocates for the adoption of climate-smart agricultural practices, enhancement of irrigation infrastructure, and promotion of sustainable pesticide management, offering actionable insights for policymakers to devise adaptive strategies that bolster resilience and productivity in Nepal's rice sector.

Keywords*:* Climate Change; Rice Yield; ARDL Model; Nepal Agriculture; Temperature; Rainfall; Pesticide Use

INTRODUCTION

Rice, a staple food for more than half of the global population, plays a pivotal role in ensuring food security, particularly in agrarian economies like Nepal. However, the productivity of rice is highly sensitive to climatic factors such as temperature, rainfall, and extreme weather events. The interplay between climate variability and agricultural practices poses significant challenges to achieving consistent and sustainable rice yields. This issue is not unique to Nepal but is part of a broader regional concern, as seen in countries like Bangladesh, India, and Sri Lanka, where climate-induced changes in rainfall and temperature have been interconnected to fluctuating rice production patterns (Auffhammer et al., 2012; Alam et al., 2023; Ratnayake et al., 2023).

The relationship between climate change and rice yield is complex, with impacts varying across different geographic regions and climatic zones. For instance, studies in Bangladesh have shown that increased temperature during the critical growing phases of rice can significantly reduce yield, while erratic rainfall patterns exacerbate the issue by disrupting irrigation systems and soil moisture balance (Rimi et al., 2009; Sarker et al., 2012). Similar findings have been reported in Nepal, where agro-climatic variability in the Terai region has led to substantial year-to-year yield fluctuations (Bista, 2023; Amgain et al., 2024).

Agricultural practices also play a critical role in either mitigating or exacerbating the effects of climatic changes. Effective adaptation measures, such as improved irrigation techniques, resilient crop varieties, and optimized planting schedules, have been shown to alleviate some of the negative impacts of climate variability on rice production (Upendram et al., 2023; Thapa & Chand, 2024). In Nepal, where traditional farming methods dominate, understanding the synergies between climate factors and agricultural practices is crucial for developing sustainable strategies to enhance rice productivity.

Several studies have highlighted the complicated relationship between climate variables and rice yield, providing valuable insights into how temperature and rainfall shape agricultural productivity. Khan and Jadaun (2023) emphasized the joint impacts of rainfall and temperature on rice yield in India, advocating for a combined analysis to account for their complex interactions. Similarly, Mahmood et al. (2012) demonstrated the significant effects of both rainfall and temperature on rice productivity in the wheat-rice cropping systems of Punjab, highlighting the importance of understanding regional climatic dynamics. Building on this, Chen et al. (2023) revealed that these climate-yield relationships are not static, showing temporal variations since 1925 that call for adaptive approaches to agricultural planning. In the context of Nepal, Dhungel (2024) examined the vulnerability of farming communities in the Bhaktapur district to climate change, emphasizing the need for region-specific strategies to mitigate adverse impacts. Complementing these studies, James et al. (2018) applied the ARDL model to assess climate change's effects on rice production in Kebbi State, underscoring the importance of dynamic modeling techniques to capture both long and short -run effects. Together, these studies underscore the need for integrated and localized approaches to address the multifaceted challenges posed by climate variability on rice production, particularly in vulnerable regions like Nepal.

Studies from similar contexts (Auffhammer et al., 2012; Alam et al., 2023) emphasize temperature and rainfall as key determinants, but the interaction with agricultural practices requires further investigation. Understanding these dynamics is critical for creating evidence-based policies to enhance sustainable rice production and address climate-related risks.

This study investigates the long and short-run impacts of climatic factors (temperature, rainfall) and agricultural practices (pesticide usage) on rice yield in Nepal using the ARDL model. It aims to analyze how these variables interact over the past three decades, providing insights for climate-resilient and sustainable rice production strategies.

Literature Review

1. Impact of Climate Change on Rice Yield

The relationship between climate change and rice production has been a focal point in agricultural research. Studies have consistently highlighted temperature and rainfall variability as key determinants of rice yield. For instance, Alam et al. (2023) demonstrated that temperature and rainfall fluctuations significantly impact rice production in Bangladesh, with increasing temperature during critical growth stages leading to lower yields. Similarly, Auffhammer et al. (2012) found that monsoonal rainfall variability critically affects rice yields in India, emphasizing the vulnerability of rain-fed agriculture to changing climatic conditions. Research in Sri Lanka by Ratnayake et al. (2023) also underscores how erratic rainfall patterns and rising temperatures disrupt traditional paddy farming systems.

In the Nepalese context, Bhatta et al. (2024) revealed that greenhouse gas emissions and climate variability, particularly precipitation changes, have significant implications for rice productivity. Amgain et al. (2024) supported these findings, demonstrating that agro-climatic variability in the western Terai region of Nepal has resulted in yield fluctuations, particularly in years with extreme climatic events.

2. Temperature Effects on Rice Yield

Temperature is one of the most critical factors influencing rice growth and yield. Rimi et al. (2009) and Sarker et al. (2012) in Bangladesh have shown that even small increases in temperature during sensitive growth periods, such as flowering and grain filling, can result in significant yield reductions. Similar outcomes were observed by Bhatt et al. (2019), who reported that high temperatures during these critical phases in Uttar Pradesh, India, negatively impacted rice yields.

In Nepal, Thapa and Chand (2024) analyzed temperature trends and their impacts on irrigation requirements, finding that rising temperatures exacerbate water stress for rice cultivation. Additionally, Dahal et al. (2024) highlighted that increasing temperatures in the Koshi River Basin have contributed to drought conditions, adversely affecting rice production.

3. Rainfall Variability and Rice Yield

Rainfall variability significantly influences rice productivity, particularly in regions dependent on monsoonal precipitation. Research by Chowdhury and Khan (2015) in Bangladesh showed that erratic rainfall patterns disrupt planting schedules and reduce yields. Similar findings were reported by Jaiswal et al. (2023), who analyzed rainfall extremes in India and their implications for water requirements in rice farming.

In Nepal, Bista (2023) forecasted rainfall variability trends, emphasizing their potential risks to rice production. Thapa and Chand (2024) also reported that insufficient or delayed rainfall in the Chandra Canal Irrigation System leads to yield declines, particularly for smallholder farmers who lack access to alternative water sources.

4. Role of Agricultural Inputs in Rice Yield

The use of agricultural inputs such as pesticides and fertilizers has been explored as a potential mitigating factor against climate-induced yield losses. Studies by Mainuddin et al. (2022) and Upendram et al. (2023) in Bangladesh and Nepal, respectively, highlighted the role of improved agricultural practices in enhancing rice productivity under changing climatic conditions. Similarly, Abbas and Dastgeer (2021) found that higher pesticide usage positively influenced rice yields in Punjab, Pakistan, but emphasized the need for balanced and sustainable practices.

In Nepal, Chandio et al. (2021) examined the combined effects of climatic and technological factors on rice yield, showing that the increased adoption of pesticides and fertilizers has helped offset some of the negative impacts of climate variability. However, excessive reliance on these inputs can lead to diminishing returns and environmental degradation, as highlighted by Thapa and Chand (2024).

5. Adaptation Strategies for Climate-Resilient Rice Farming

Adaptive measures are crucial for mitigating the impacts of climate change on rice yield. Research by Rahman et al. (2017) and Al Mamun et al. (2023) in Bangladesh suggested that adopting climate-resilient practices, such as the use of drought-tolerant rice varieties, improved irrigation techniques, and crop diversification, significantly reduces vulnerability. Similarly, Joseph et al. (2023) advocated for integrating climate-smart agriculture with policy interventions to sustain rice yield in the face of increasing climatic variability.

In Nepal, Thapa and Dhakal (2024) emphasized the importance of farmer perceptions and local knowledge in designing effective adaptation strategies. Their study found that smallholder farmers in Chitwan have adopted various coping mechanisms, such as adjusting planting schedules and adopting new rice varieties, to combat climate risks.

6. Regional Comparisons and Synthesis

While the impacts of climate change on rice yield are evident across South Asia, regional variations highlight the importance of localized studies. For example, Mohapatra et al. (2024) in India, Zhang et al. (2023) in Malaysia, and Hussain (2024) in Pakistan all reported significant regional differences in how climatic and non-climatic factors influence rice production. These findings underscore the need for region-specific strategies that address local climatic conditions, resource availability, and socio-economic contexts.

In Nepal, research by Joshi et al. (2023) and Adhikari and Dahal (2023), Kumar (2024). has started to fill this gap, providing valuable insights into the unique challenges faced by Nepalese farmers. However, more empirical studies are needed to develop comprehensive models that integrate climate variables with agricultural practices, as highlighted by GC and Jun-Ho (2023).

Summary of Literature Review

The literature reveals a complex interplay between climate factors and agricultural practices in determining rice yield. While temperature and rainfall variability remain critical determinants, agricultural inputs and adaptation strategies play an essential role in mitigating adverse impacts. In Nepal, a deeper understanding of these dynamics is crucial for developing evidence-based policies and interventions to ensure sustainable rice yield in the face of climate variation. This study contributes to this growing body of knowledge by focusing on the Nepalese context, using an ARDL model to explore the long and short-run connections between rice yield, climatic factors, and agricultural practices.

Literature Gap

Despite extensive research on the relationship between climate change and rice production globally, significant gaps remain in the context of Nepal. Studies from Bangladesh (Rimi et al., 2009; Alam et al., 2023), India (Auffhammer et al., 2012; Mohapatra et al., 2024), and Sri Lanka (Ratnayake et al., 2023) highlight climatic factors like temperature and rainfall but fail to address Nepal's unique agro-climatic zones, farming practices, and socio-economic conditions. The role of agricultural inputs, such as pesticide use, and their interplay with climatic factors is underexplored, while existing research often relies on descriptive analyses rather than econometric models like ARDL to capture dynamic relationships. Short-term impacts and specific climatic events dominate the literature, leaving gaps in understanding long-term trends and the combined effects of climatic and non-climatic factors, such as irrigation and pesticide use (Bista, 2023; Joshi et al., 2023; Adhikari & Dahal, 2023). Moreover, the use of advanced tools like remote sensing and machine learning is limited in Nepal, despite their potential to uncover spatio-temporal variability (Islam et al., 2023; Zhang et al., 2023). This study aims to fill these gaps by employing an ARDL model to analyze the long and short- run impacts of temperature, rainfall, and pesticide use on rice yield in Nepal, contributing to evidence-based strategies for sustainable and climate-resilient rice production.

METHODS

Research Design

This quantitative study investigates the long-term and short-term effects of climatic factors (temperature, rainfall) and agricultural practices (pesticide usage) on rice yield in Nepal. The research utilizes an analytical and descriptive design, employing the Autoregressive Distributed Lag (ARDL) model to analyze time-series data. This approach is well-suited for identifying both short-run dynamics and long-run equilibrium relationships among variables, accommodating mixed orders of integration (I(0) and I(1)).

Data Collection and Sources

The study uses secondary data from 1990 to 2022, sourced from reputable databases such as the Food and Agriculture Organization (FAO, 2024) and the Climate Change Knowledge Portal (CCKP, 2024). The variables examined include rice yield, temperature, rainfall, and pesticide usage. The selection of variables is based on their theoretical relevance and empirical evidence from prior research. Table 1 provides a summary of the variables, symbols, units, and sources.

Table 1. ***Variables, Symbols, Units, and Data Sources Used in the Study***

Variable Names	Symbols	Units	Source
Rice Yield	Rice Yield	Hectograms per hectare (hg/ha)	FAO
Average Temperature	Temperature	Degrees Celsius (°C)	CCKP
Total Rainfall	Rainfall	Millimeters (mm)	CCKP
Pesticide Usage	Pesticides	Tonnes	CCKP

Model Specification

The ARDL model is specified as follows:

$$Y_t = \beta_0 + \sum_{i=1}^{p} \beta_i \, Y_{t-i} + \sum_{j=0}^{q} \alpha_j \, X_{t-j} + \epsilon_t \qquad (1)$$

Where,

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

X_{t-j} represents the independent variables (Temperature, Rainfall ,and Pesticides.

β_0 is the constant term,

β_i and α_j are the 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.

Econometric Analysis

The ARDL model is utilized for its flexibility in handling variables integrated at different levels (Pesaran & Shin, 1995). The methodology begins with stationarity testing using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests to ensure variables are not integrated at order I(2) (Poudel et al., 2024). Optimal lag lengths are determined through criteria like the Akaike Information Criterion (AIC), ensuring appropriate lag structures for robust analysis (Pesaran et al., 2001). Bounds testing is employed to identify long-run relationships among variables, followed by the estimation of long-run coefficients to assess the persistent impacts of independent variables (Pesaran et al., 2001). The Error Correction Model (ECM) captures short-term dynamics and the speed of adjustment towards equilibrium, highlighting the significance of both short-run and long-run interactions (Pesaran & Shin, 1995).

To ensure the reliability of results, diagnostic tests are conducted, including the Jarque-Bera test for normality, the Breusch-Godfrey test for serial correlation, the Breusch-Pagan test for heteroscedasticity, and the Ramsey RESET test for model specification (Poudel et al., 2024). Stability of model parameters is validated using CUSUM and CUSUMSQ tests, ensuring consistency over time. These rigorous procedures, supported by established econometric principles, enhance the reliability and robustness of the findings, offering valuable insights into the dynamics influencing rice yield in Nepal.

Assumptions and Limitations

i. It is assumed that the data are accurately reported and free from measurement errors.

ii. The ARDL model assumes linear relationships among variables, which may not fully capture nonlinear dynamics.

iii. External factors such as policy changes or market shocks, which may influence maize yield, are not explicitly accounted for in the model.

RESULTS

Trends in Key Variables for the Analysis

The trends in key variables, including rice yield, temperature, rainfall, and pesticide usage, highlight significant fluctuations over the study period (1990-2022). These variations reflect the interplay between climatic factors and agricultural practices, underscoring their impact on rice productivity in Nepal.

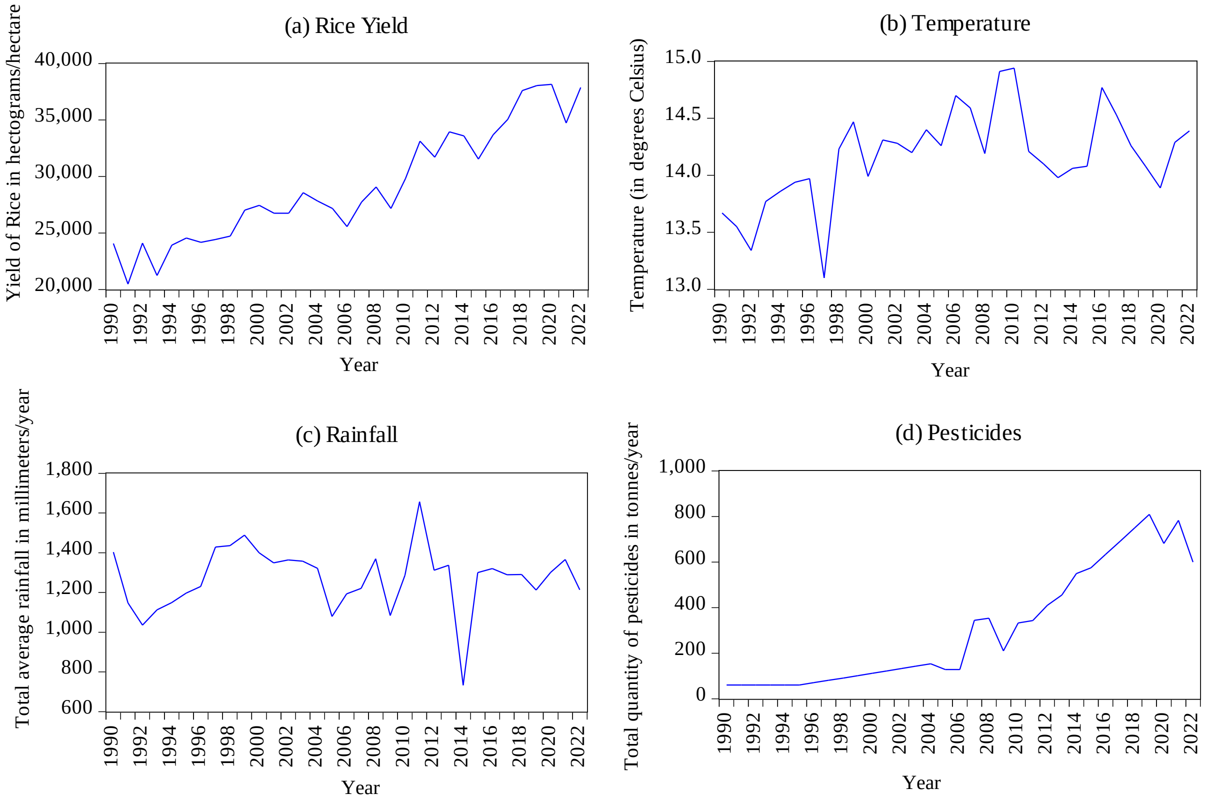

Figure 1. ***Trends in Rice Yield, Temperature, Rainfall, and Pesticide Usage (1990-2022)***

Figure 1(a) illustrates the trend in rice yield in Nepal from 1990 to 2022, showcasing a steady upward trajectory with some fluctuations. The increasing yield suggests improvements in agricultural practices and the adoption of inputs like fertilizers and pesticides over the years. However, periodic fluctuations indicate the sensitivity of rice production to external factors, particularly climatic variability. Figure 1(b) shows the trend in average temperature, which exhibits a slight but consistent rise over the study period. This gradual increase in temperature, especially during critical growth stages, could negatively affect rice yields. Figure 1(c) highlights rainfall trends, revealing significant inter-annual variability with irregular patterns. Such variability can disrupt planting schedules and soil moisture levels, directly impacting rice productivity. Finally, Figure 1(d) illustrates a sharp upward trend in pesticide usage, reflecting intensified agricultural practices aimed at mitigating challenges such as pest infestations. While increasing pesticide use may support productivity, excessive reliance raises concerns about environmental sustainability and diminishing returns. Together, these figures underscore the complex interplay between climatic factors and agricultural practices in shaping rice production outcomes in Nepal.

Descriptive Statistics

The descriptive statistics, as shown in Table 2, highlight significant variability in key variables such as rice yield, temperature, rainfall, and pesticide usage over the study period.

Table 2. ***Descriptive Statistics of Key Variables***

	Rice Yield	Temperature	Rainfall	Pesticides
Mean	29141.03	14.16	1271.93	307.31
Median	27750.00	14.20	1300.03	153.00
Maximum	38153.00	14.94	1656.02	809.09
Minimum	20481.00	13.10	732.86	60.11
Std. Dev.	5042.15	0.41	161.20	256.90
Skewness	0.35	-0.35	-0.83	0.66
Kurtosis	2.07	3.39	5.62	1.93
Observations	33	33	33	33

Table 2 presents the descriptive statistics of the key variables analyzed in the study, including rice yield, temperature, rainfall, and pesticide usage. The mean rice yield is 29,141.03 hg/ha, with a standard deviation of 5,042.15 hg/ha, reflecting moderate variability around the mean, while the range spans from a minimum of 20,481 hg/ha to a maximum of 38,153 hg/ha. The average temperature is 14.16°C, with minimal variation as indicated by a standard deviation of 0.41°C, ranging between 13.10°C and 14.94°C. Rainfall exhibits greater variability, with a mean of 1,271.93 mm, a standard deviation of 161.20 mm, and a range from 732.86 mm to 1,656.02 mm, showing the impact of climatic fluctuations. Pesticide usage shows a wide disparity, with a mean of 307.31 tonnes, a standard deviation of 256.90 tonnes, and a range from 60.11 tonnes to 809.09 tonnes, indicating the intensification of agricultural inputs over the years. Skewness values indicate slight asymmetry in the distributions, with rice yield and pesticides positively skewed, while temperature and rainfall show negative skewness. Kurtosis values suggest that rainfall exhibits a leptokurtic distribution (5.62), indicating heavy tails, whereas the other variables are closer to a normal distribution. These descriptive statistics provide an overview of the data's variability and distribution, which is crucial for understanding the dynamics of rice production.

Table 3. ***Correlation Analysis***

	Rice Yield	Temperature	Rainfall	Pesticides
Rice Yield	1.00			
Temperature	0.34	1.00		
Rainfall	0.09	0.07	1.00	
Pesticides	0.93	0.30	-0.02	1.00

Table 3 presents the correlation analysis among the key variables—rice yield, temperature, rainfall, and pesticide usage—providing insights into their linear relationships. Rice yield shows a strong positive correlation with pesticide usage ($r=0.93$), suggesting that increased pesticide application is closely associated with higher rice yields, likely due to its role in controlling pests and enhancing productivity. The correlation between rice yield and temperature is moderately positive ($r=0.34$), indicating that higher temperatures, within the observed range, may have a limited favorable impact on rice yield, though this relationship might vary during extreme conditions. The relationship between rice yield and rainfall is weakly positive ($r=0.09$), reflecting minimal influence, which could be attributed to the interplay of irrigation practices mitigating rainfall dependency. Interestingly, temperature and rainfall exhibit a weak correlation ($r=0.07$), suggesting minimal direct interaction between these climatic factors within the dataset. Pesticide usage is weakly correlated with temperature ($r=0.30$) and shows a negligible negative correlation with rainfall ($r=-0.02$), indicating that pesticide application is less dependent on climatic factors. These correlation coefficients provide a foundational understanding of how these variables relate to each other, setting the stage for further econometric analysis to explore causal relationships and dynamics.

Unit Root Testing

Table 4 presents the results of unit root tests conducted to examine the stationarity of key variables. The tests confirm that all variables are either stationary at level or become stationary after first differencing, satisfying the requirements for ARDL modeling.

Table 4. ***Unit Root Test Results***

UNIT ROOT TEST TABLE (PP)

At Level		Rice Yield	Temperature	Rainfall	Pesticides
With Const.	t-Stat.	0.05	-3.07**	-4.61***	-0.52
With Const.& T.	t-Stat.	-4.55***	-3.58**	-4.56***	-2.34
None	t-Stat.	3.25	0.67	-0.56	0.82
At First Difference		d(Rice Yield)	d(Temperature)	d(Rainfall)	d(Pesticides)
With Const.	t-Stat.	-13.98***	-10.26***	-19.97***	-6.69***
With Const. & T.	t-Stat.	-14.21***	-15.50***	-19.44***	-6.56***
None	t-Stat.	-8.10***	-9.73***	-20.36***	-6.19***

UNIT ROOT TEST TABLE (ADF)

At Level		Rice Yield	Temperature	Rainfall	Pesticides
With Const.	t-Stat.	-0.65	-3.22**	-4.61***	-0.67
With Const.& T.	t-Stat.	-4.52***	-3.64**	-4.56***	-2.46
None	t-Stat.	1.09	0.23	-0.24	0.55
At First Difference		d(Rice Yield)	d(Temperature)	d(Rainfall)	d(Pesticides)
With Const.	t-Stat	-8.93***	-6.56***	-8.16***	-6.68***
With Const. & T.	t-Stat.	-8.77***	-6.66***	-8.00***	-6.55***
None	t-Stat.	-8.13***	-6.59***	-8.30***	-6.17***

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

The results of the unit root tests using the Phillips-Perron (PP) method reveal the stationarity properties of the key variables. At the level, with a constant term, temperature ($t=-3.07$) is stationary at the 5% significance level, and rainfall ($t=-4.61$) is stationary at the 1% level, while rice yield ($t=0.05$) and pesticides ($t=-0.52$) are non-stationary. When both constant and trend are included, rice yield ($t=-4.55$), temperature ($t=-3.58$), and rainfall ($t=-4.56$) become stationary at the 1% and 5% levels, while pesticides ($t=-2.34$) remain non-stationary. Without any deterministic components, none of the variables exhibit stationarity at the level. However, at first differences, all variables—rice yield ($t=-13.98$), temperature ($t=-10.26$), rainfall ($t=-19.97$), and pesticides ($t=-6.69$)—

become stationary at the 1% significance level under all conditions (constant, constant with trend, and none). These results confirm that while some variables are stationary at the level, all variables achieve stationarity after first differencing, validating the suitability of the ARDL model, which accommodates variables integrated at I(0) and I(1). This ensures the robustness and validity of the subsequent analysis.

Lag Length Selection

Table 5 displays the criteria of lag length selection for the ARDL model, with the AIC identifying an optimal lag of 1. This ensures the inclusion of appropriate lag structures for robust long-run and short-run analysis (Poudel et al., 2024a).

Table 5. ***Criteria of Lag Length Selection***

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-653.6787	NA	5.87e+14	45.35715	45.54574	45.41621
1	-599.4122	89.82035*	4.25e+13*	42.71808*	43.66105*	43.01341*
2	-590.2669	12.61425	7.32e+13	43.19082	44.88815	43.72240
3	-573.0747	18.97072	8.15e+13	43.10860	45.56030	43.87644
4	-554.8809	15.05691	1.06e+14	42.95730	46.16338	43.96141

Table 5 presents the criteria for selecting the optimal lag length for the ARDL model, which is crucial for ensuring accurate long-run and short-run estimates. Various selection criteria, including the Log-Likelihood (LogL), Likelihood Ratio (LR), Final Prediction Error (FPE), AIC, Schwarz Criterion (SC), and Hannan-Quinn Criterion (HQ), were employed. The optimal lag length is determined based on the lowest values of AIC, SC, and HQ, which minimize information loss and improve model fit. At lag 1, the AIC (42.72), SC (43.66), and HQ (43.01) achieve their minimum values, and the LR test (89.82) confirms the statistical significance of adding the lag. Consequently, lag 1 is selected as the optimal lag for the ARDL model, ensuring robust modeling of the short-run dynamics and long-run equilibrium relationships among the variables.

ARDL 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

20.52321 exceeds the critical bounds at all significance levels, validating cointegration (Pesaran et al., 2001).

Table 6. ***ARDL Bounds Test Results***

Test Statistic	Value	Significant	I(0)	I(1)
Asymptotic: n=1000				
F-statistic	6.873676			
k	3	5%	2.79	3.67
Actual Sample Size	32			Finite Sample: n=35
		5%	3.164	4.194
Finite Sample: n=30				
		5%	3.272	4.306

Table 6 presents the results of the ARDL bounds test, which is used to determine the presence of a long-run equilibrium relationship among the variables. The computed F-statistic (6.87) exceeds the upper critical value (I(1)) across all significance levels (5%) for both asymptotic and finite sample critical values. Specifically, for an actual sample size of 32, the critical bounds at the 5% significance level are I(0)=3.16 and I(1)=4.19, while for n=30, the bounds are I(0)=3.27 and I(1)=4.31. Since the F-statistic surpasses these upper bounds, the null hypothesis of no cointegration is rejected, confirming the existence of a significant long-run relationship among the variables. This result validates the use of the ARDL approach for analyzing both short- and long-term dynamics in the study.

Table 7. ***Short Run Coefficients***

Variable	Coefficient	Std. Error	t-Statistic	Prob.
d(Temperature)	-369.7304	611.4687	-0.604660	0.5511
d(Rainfall)	1.471133	1.148470	1.280950	0.2125
d(Pesticides)	5.247882	3.188650	1.645801	0.1128
CointEq(-1)*	-0.852543	0.134637	-6.332175	0.0000

Table 7 presents the short-run coefficients from the ARDL model, highlighting the immediate effects of the independent variables on rice yield. The error correction term (CointEq(−1)=−0.8525) is negative and highly significant (p<1%), indicating a robust adjustment process where approximately 85.25% of deviations from the long-run equilibrium are corrected in the subsequent period. This strong adjustment mechanism underscores the model's validity in capturing short-term dynamics while ensuring convergence towards the long-run equilibrium. The results emphasize the critical role of long-term relationships in understanding the impacts of climatic factors and agricultural practices on rice yield.

Long Run Coefficients

The long-run coefficients indicate that rainfall, temperature, and pesticide usage significantly impact rice yield in Nepal, with positive effects observed for all three variables. These results highlight the importance of sustainable agricultural practices and climate-resilient strategies to optimize productivity.

Table 8. ***Long Run Coefficients of Key Variables***

Variable	Coeff.	Standard Error	t-Stat.	p-value
Temperature	2181.478	991.8548	2.199392	0.0377
Rainfall	5.100482	2.484098	2.053253	0.0511
Pesticides	17.70265	1.251508	14.14506	0.0000
C	-13360.69	13622.83	-0.980758	0.3365

Table 8 highlights the long-run impacts of temperature, rainfall, and pesticide usage on rice yield in Nepal, offering valuable insights for sustainable agricultural practices and policy interventions. Temperature shows a positive and statistically significant effect (Coefficient=2181.48, $p = 0.037$), suggesting that within the observed range, moderate warming may enhance rice productivity, possibly by extending the growing season or improving physiological processes. However, this benefit is conditional on temperature increases remaining within critical thresholds, as excessive warming could negate these gains. Rainfall also has a positive and marginally significant impact (Coefficient=5.10, $p = 0.05$), reflecting its importance in maintaining soil moisture and supporting crop growth, particularly in rain-fed systems. The modest magnitude, however, indicates that irrigation systems may play a mitigating role in addressing rainfall variability. Pesticide usage shows the strongest positive effect (Coefficient=17.70, $p < 1$), emphasizing its critical role in combating pest-related losses and boosting productivity. Nonetheless, over-reliance on pesticides poses environmental and economic risks, underscoring the need for integrated pest management practices to ensure long-term sustainability. Together, these findings highlight the importance of climate-smart agriculture, improved irrigation infrastructure, and sustainable input management to build a resilient rice production system in Nepal.

The Wald Test

The Wald Test in Table 9 evaluates the joint significance of temperature, rainfall, and pesticide usage in the model. It assesses whether these variables collectively contribute to explaining variations in rice yield over time.

Table 9. ***Wald Test Results for Joint Significance of Variables***

Test Statistic	Value	Df	Probability
F-statistic	6.160299	(6, 24)	0.0005
Chi-square	36.96179	6	0.0000
H_0: C(2)=C(3)=C(4)=C(5)=C(6)=C(7)=0		H_0 Summary	
Normalized Restriction (= 0)		Value	Std. Err.
C(2)= Temperature		-369.7304	740.2764
C(3) = Temperature(-1)		2229.534	784.1442
C(4) = Rainfall		1.471133	1.670976
C(5) = Rainfall(-1)		2.877246	1.706335
C(6) = Pesticides		5.247882	3.827120
C(7) = Pesticides(-1)		9.844383	4.028710

Table 9 presents the Wald Test results, which assess the joint significance of the explanatory variables—temperature, rainfall, and pesticide usage—in influencing rice yield. The results, with an F-statistic of 6.16 (p=0.0005) and a Chi-square statistic of 36.96 (p< 1%), strongly reject the null hypothesis (H0) that the coefficients of these variables are collectively equal to zero. This confirms that these factors jointly have a significant impact on rice yield, underscoring their critical role in agricultural productivity.

The coefficients for temperature and its lagged term (C(2)=−369.73, C(3) = 2229.53) suggest that while immediate changes in temperature may not favor rice yield, lagged effects are significantly positive. This indicates that moderate increases in temperature over time could enhance productivity, possibly by extending the growing season or improving crop physiology. However, the potential for extreme temperatures to harm yields emphasizes the need for adaptive measures, such as the development and adoption of temperature-resilient rice varieties.

Rainfall and its lagged term (C(4)=1.47, C(5) = 2.88) show a sustained positive impact on rice yield, highlighting the importance of adequate rainfall in maintaining soil moisture and supporting growth, particularly in rain-fed systems. This relationship underscores the need for improved water management practices and enhanced irrigation infrastructure to mitigate the risks of rainfall variability and optimize its benefits for agriculture.

Pesticide usage and its lagged term (C(6)=5.25 , C(7) = 9.84) exhibit a strong positive influence on rice yield, demonstrating the critical role of pesticides in managing pest pressures and enhancing productivity. However, excessive reliance on chemical inputs can lead to environmental degradation, health risks, and diminishing returns over time. Implementing integrated pest management (IPM) practices and promoting sustainable use of pesticides are essential for balancing productivity gains with ecological health.

In economic terms, the Wald Test highlights the collective importance of climatic and non-climatic factors in determining rice yield, emphasizing the need for holistic and strategic policy interventions. Investments in climate-smart agriculture, water resource management, and sustainable agricultural practices can bolster resilience and productivity. These measures, coupled with long-term planning, can help optimize rice production and ensure food security in Nepal amidst increasing climatic uncertainties.

Granger Causality Test

The Granger Causality Test in Table 10 examines the directional relationships between rice yield, temperature, rainfall, and pesticide usage. It identifies whether changes in these variables can predict future variations in rice yield, providing insights into their causative influence.   .

Table 10. *Results of Granger Causality Test*

H0	Observations	F-Stat.	Probability
Temperature →Rice Yield	32	7.75645	0.0093
Rice Yield →Temperature		0.58216	0.4516
Rainfall →Rice Yield	32	0.02730	0.8699
Rice Yield →Rainfall		0.00431	0.9481
Pesticides →Rice Yield	32	11.2476	0.0022
Rice Yield →Pesticides		2.44700	0.1286

Table 10 presents the Granger Causality Test results, revealing the predictive relationships between rice yield, temperature, rainfall, and pesticide usage. Temperature is found to Granger-cause rice yield (F=7.76, p < 1%), indicating that changes in temperature significantly predict variations in rice yield. This underscores the critical role of climatic conditions in agricultural productivity and highlights the need for strategies such as temperature-resilient crop varieties and adaptive farming practices to mitigate adverse impacts. Rainfall, however, does not Granger-cause rice yield (F=0.03, p = 0.86), suggesting that irrigation systems may mitigate the dependency on rainfall variability. Pesticide usage significantly Granger-causes rice yield (F=11.25, p < 1%), emphasizing its importance in managing pests and enhancing productivity. However, rice yield does not Granger-cause temperature, rainfall, or pesticide usage, reaffirming that these factors are primarily exogenous influences on agricultural output. These findings highlight the importance of integrating climate-smart agriculture, robust irrigation infrastructure, and sustainable pesticide management to address climatic variability and enhance rice production sustainably in Nepal.

Stability and Diagnostics Tests

Table 11 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 11. ***Diagnostics and Stability Tests***

Diagnostics	**Statistics**	**p-value**
Normality(J-B)	5.63	0.06
Serial Correlation $\chi^2(2)$	1.08	0.58
B-P-G Test(Scaled explained SS)	4.85	0.68
Ramsey RESET(F_{STAT})	0.04	0.8378
CUSUM Test	Stable	
CUSUM of Square Test	Stable	

Table 11 provides the results of diagnostics and stability tests, confirming the reliability of the econometric model used in this study. The JB test (p=0.06) indicates that the residuals are approximately normally distributed, ensuring valid statistical inference (See Figure 2). The Breusch-Godfrey test for serial correlation ($\chi2(2)=1.08, p=0.58$) reveals no evidence of serial correlation, confirming that the error terms are independent across observations (See Table 12). The BPG test for heteroscedasticity (p=0.68) indicates constant variance of residuals, enhancing the reliability of standard errors (See Table 13). The Ramsey RESET test (p=0.84) suggests no specification errors, such as omitted variables or incorrect functional form, affirming the model's accuracy in capturing the relationships among the variables (See Table 14). Finally, the CUSUM and CUSUMSQ tests confirm the stability of the model's parameters over time, ensuring consistency in the relationships and making the model a reliable tool for long-term forecasting and policy analysis (See Figure 3 & Figure 4). These results validate the robustness of the model and its suitability for understanding the economic impacts of climatic and agricultural factors on rice production in Nepal.

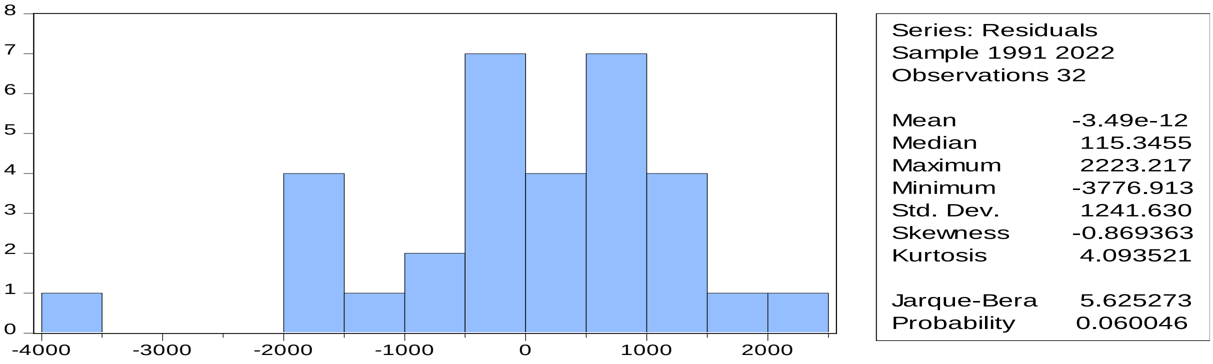

Figure 2. ***Histogram of Residuals for Normality Test***

Table 12. ***Breusch-Godfrey Serial Correlation LM Test Results***

F-stat.	0.385763	Probability F(2,22)	0.6844
Obs*R^2	1.084198	Probability Chi-Square(2)	0.5815

Table 13. ***Heteroskedasticity Test Results Using BPG Method***

F-stat.	0.722817	Probability F(7,24)	0.6541
Obs*R^2	5.571666	Probability Chi-Square(7)	0.5906
Scaled explained SS	4.847644	Probability Chi-Square(7)	0.6785

Table 14. ***Ramsey RESET Test Results for Model Specification***

	Value	Degree of freedom	Prob.
t-stat.	0.206989	23	0.8378
F-stat.	0.042845	(1, 23)	0.8378

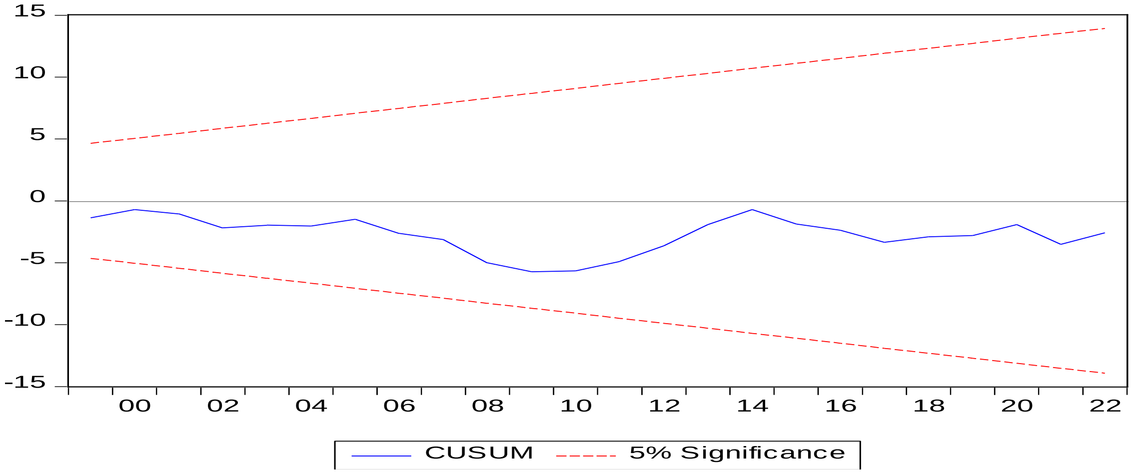

Figure 3. ***CUSUM Test for Stability of Model Parameters***

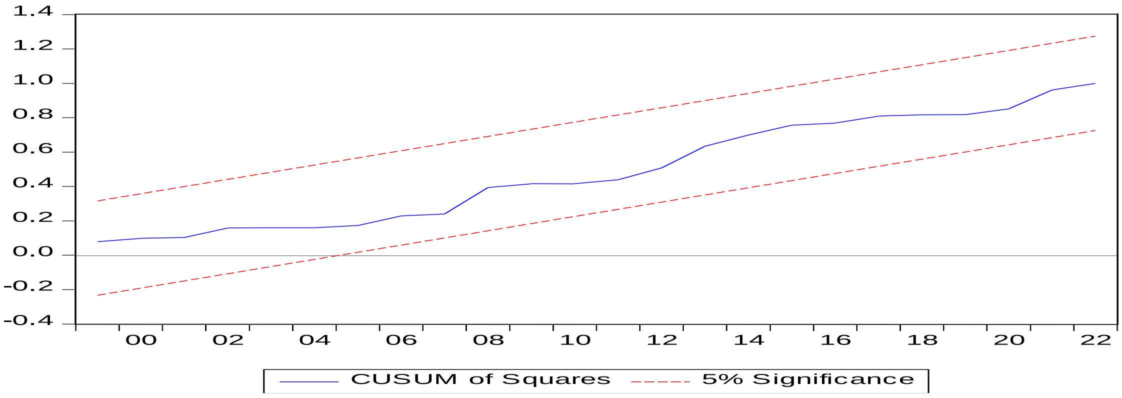

Figure 4. ***CUSUM of Squares Test for Stability of Model Parameters***

DISCUSSION

This research critically analyzes the impact of climatic factors such as rainfall and temperature, alongside agricultural practices like pesticide usage, on rice yield in Nepal, using an ARDL model to explore both long and short-run dynamics. The findings, when compared to past research, offer valuable insights into regional and context-specific variations. Consistent with Alam et al. (2023), this study demonstrates the significant role of temperature in influencing rice yield, with both long and short-run effects. While Alam et al.(2023) reported that higher temperatures during critical growth phases reduced yield in Bangladesh, this study highlights a positive long-term impact of moderate temperature increases in Nepal, possibly due to adaptation strategies and improved physiological conditions for rice growth. Similarly, Bhatt et al. (2019) documented negative impacts of high temperatures on rice production in Uttar Pradesh, India, but this study identifies lagged positive effects, suggesting that controlled warming within thresholds might support productivity in Nepal.

Rainfall's role aligns with findings by Jaiswal et al. (2023), where adequate rainfall was crucial for rice farming in India’s rain-fed systems. However, the results from Nepal indicate marginal significance, which may reflect the mitigating influence of irrigation systems. Diverging from Ratnayake et al. (2023), who reported erratic rainfall disrupting paddy farming in Sri Lanka, this study underscores the importance of irrigation infrastructure in reducing dependency on rainfall variability in Nepal. The strong positive association between pesticide usage and rice yield in this study mirrors findings by Abbas and Dastgeer (2021), who emphasized the role of pesticides in managing pest pressures. Similarly, Chandio et al. (2021) highlighted that technological inputs, including pesticides, offset the adverse effects of climate variability. However, this study raises concerns about over-reliance on chemical inputs, stressing the need for integrated pest management strategies.

Adaptation measures such as adjusting planting schedules and adopting climate-resilient varieties, as discussed by Thapa and Dhakal (2024), are supported by the findings of this study, which demonstrate their role in mitigating the effects of rainfall and temperature variability. Al Mamun et al. (2023) emphasized the importance of drought-tolerant rice varieties and improved irrigation systems in Bangladesh, and similar strategies appear effective in the Nepalese context. Regional comparisons with Mohapatra et al. (2024) in India and Zhang et al. (2023) in Malaysia highlight the necessity of localized interventions. This study reinforces these conclusions, emphasizing that Nepal's unique agro-climatic zones require tailored strategies distinct from neighboring regions.

The findings also align with Rahman et al. (2017), who identified a long-term equilibrium link between climatic variables and agricultural productivity, underscoring the need for integrated approaches to sustain rice yield. While Bhatta et al. (2024) noted immediate adverse effects of climatic shocks in Nepal, this study reveals a robust error correction mechanism, reflecting resilience in Nepalese farming systems and rapid adjustments to equilibrium. Al Mamun et al. (2023) advocated for using dynamic econometric models to capture complex interactions, a methodological gap this study addresses through its application of the ARDL framework. Concerns about environmental degradation from excessive pesticide use, highlighted by Mainuddin et al. (2022) in Bangladesh, are echoed here, reinforcing the urgency of sustainable practices. Additionally, Amgain et al. (2024) used simulation models to forecast agro-climatic impacts in Nepal's Terai region. While this study focuses on historical data, its findings complement these forecasts by providing empirical evidence to validate future risk scenarios.

This research contextualizes findings within Nepal's agro-climatic and agricultural framework, adding to the existing literature. The results emphasize the importance of integrated interventions such as climate-smart agriculture, sustainable pesticide management, and enhanced irrigation systems to ensure resilience and productivity in rice farming amidst climatic uncertainties. By bridging methodological and contextual gaps, this study provides actionable insights for policymakers and stakeholders.

CONCLUSION

This research explores the impact of climatic factors such as temperature and rainfall and agricultural practices, particularly pesticide usage, on rice yield in Nepal using an ARDL model. The findings highlight the significant role of these variables in shaping both short and long-term rice productivity. Temperature exhibits a positive long-term effect, suggesting potential benefits within moderate thresholds, while rainfall, although marginally significant, underscores the need for robust irrigation systems to mitigate variability. Pesticide usage demonstrates a strong positive influence, reflecting its critical role in addressing pest-related challenges but also raising concerns about sustainability. These results emphasize the importance of adaptive strategies and integrated approaches to enhance climate resilience and ensure sustainable rice production in Nepal. The implications of this study are multifaceted and critical for policymakers, researchers, and practitioners. For policymakers, the evidence underscores the need for investments in climate-smart agricultural practices, including the development of temperature-resilient rice varieties and efficient irrigation systems. Sustainable pesticide management practices, such as integrated pest management, are crucial to balance productivity with environmental sustainability. Researchers can leverage these findings to build predictive models and design interventions targeting regional climatic and agricultural challenges. For farmers, the study provides insights into the importance of aligning agricultural practices with climatic realities, promoting practices that enhance resilience and productivity.

This research adds uniquely to the existing works by contextualizing the dynamics of climatic and agricultural variables within Nepal's distinct agro-climatic zones. Unlike broader regional studies, it employs an ARDL framework to capture long and short -run relationships, providing nuanced insights into how these factors interact. The strong focus on pesticide usage, often underexplored in Nepalese studies, adds a novel dimension by highlighting its dual role as a productivity enhancer and a sustainability concern. Furthermore, the study bridges gaps in understanding the lagged effects of rainfall and temperature on rice yield, offering a fresh perspective on adaptive capacity in agriculture. Future research should focus on exploring the impact of climate extremes, such as droughts and floods, on rice yield in Nepal to better understand thresholds, vulnerabilities, and adaptive strategies.

REFERENCES

Abbas, S., & Dastgeer, G. (2021). Analysing the impacts of climate variability on the yield of Kharif rice over Punjab, Pakistan. *Natural Resources Forum*, *45*(4), 329-349. https://doi.org/10.1111/1477-8947.12230

Adhikari, A., & Dahal, S. (2023). Impact of climate change on major cereal crops production in Paripattle, Dhankuta, Nepal. *Nepalese Journal of Agricultural Sciences,24, 59-70 http://esjindex.org/search.php?id=6279*

Al Mamun, M. A., Nihad, S. A., Sarkar, M. A., Sarker, M. R., Skalicka, J., & Skalicky, M. (2023). Spatio-temporal variability of climatic variables and its impacts on rice yield in Bangladesh. *Frontiers in Sustainable Food Systems*, *7*, 1290055. https://doi.org/10.3389/fsufs.2023.1290055

Alam, E., Hridoy, A. E. E., Tusher, S. M. S. H., Islam, A. R. M. T., & Islam, M. K. (2023). Climate change in Bangladesh: Temperature and rainfall climatology of Bangladesh for 1949–2013 and its implication on rice yield. *PLOS One*, *18*(10), e0292668. https://doi.org/10.1371/journal.pone.0295718

Amgain, L., Poudel, M., Adhikari, S., & Dhakal, D. (2024). Trends of agro-climatic variability and multi-year prediction of rice and wheat yields under the changing climatic scenarios using DSSAT crop model in Nepalese western Terai. *Research on Crops*, *25*(3).

Auffhammer, M., Ramanathan, V., & Vincent, J. R. (2012). Climate change, the monsoon, and rice yield in India. *Climatic Change*, *111*, 411-424. https://doi.org/10.1007/s10584-011-0208-4

Bhatta, A. D., Panthee, K. R., & Joshi, H. P. (2024). Impact of GHG emission, temperature, and precipitation on rice production in Nepal. *Journal of Agrometeorology*, *26*(3), 305-310. https://doi.org/10.54386/jam.v26i3.2629

Bista, R. B. (2023). Forecasting climate variability in Nepal. *SAINSMAT: Journal of Applied Sciences, Mathematics, and its Education*, *12*(1), 8-20. https://doi.org/10.35877/sainsmat1150

Chandio, A. A., Jiang, Y., Ahmad, F., Adhikari, S., & Ain, Q. U. (2021). Assessing the impacts of climatic and technological factors on rice production: Empirical evidence from Nepal. *Technology in Society*, *66*, 101607. https://doi.org/10.1016/j.techsoc.2021.101607

Chen, H., Wu, Y. C., & Teng, C. Y. (2023). Temporal variation of the relationships between rice yield and climate variables since 1925. *PeerJ*, *11*, e16045. https://doi.org/10.7717/peerj.16045

Chowdhury, I. U. A., & Khan, M. A. E. (2015). The impact of climate change on rice yield in Bangladesh: A time series analysis. *Russian Journal of Agricultural and Socio-Economic Sciences*, *40*(4), 12-28.

Dahal, N. M., Xiong, D., Neupane, N., Yuan, Y., Zhang, B., Zhang, Fang, Y., Zhao, W., Yuan, Y., Wu, Y., Neupane, N., Zhang, S. & Deng, W. (2024). Spatiotemporal assessment of drought and its impacts on crop yield in the Koshi River Basin, Nepal. *Theoretical and Applied Climatology*, *155*(3), 1679-1698. https://doi.org/10.1007/s00704-023-04719-3

Dhungel, H. B. (2024). Impact of climate change on the farming community of Bhaktapur district of Nepal. *Baneshwor Campus Journal of Academia*, *3*(1), 50-62. https://doi.org/10.3126/bcja.v3i1.65496

Food and Agriculture Organization of the United Nations. (2024). FAOSTAT. Retrieved December 10, 2024, from https://www.fao.org/faostat/en/#data

GC, A., & Jun-Ho, Y. (2023). Rice production of Nepal in 2030: A forecast using autoregressive integrated moving average model. *Available at SSRN 4497103*. https://dx.doi.org/10.2139/ssrn.4497103

Hussain, Y. (2024). The impact of climate change on rice production in Punjab: An auto regression distributed lag model. *Current Agriculture Research Journal*, *12*(2). http://dx.doi.org/10.12944/CARJ.12.2.33

Islam, M. D., Di, L., Qamer, F. M., Shrestha, S., Guo, L., Lin, L., Mayer, T. J., & Phalke, A. R. (2022). Rapid rice yield estimation using integrated remote sensing and meteorological data and machine learning. *Remote Sensing*, *15*(9), 2374. https://doi.org/10.3390/rs15092374

Jaiswal, R. K., Lohani, A. K., & Galkate, R. V. (2023). Rainfall and agro related climate extremes for water requirement in paddy grown Mahanadi basin of India. *Agricultural Research*, *12*(1), 20-31. https://doi.org/10.1007/s40003-022-00629-4

James, T. O., Babayemi, A. W., Abdulmuahymin, A. S., Udomboso, C. G., & Bello, M. L. (2018). ARDL modelling of the impacts of climate change on rice production in Kebbi State. *ProfessionalStatisticians Society of Nigeria,2*, 356-361. http://ir.library.ui.edu.ng/handle/123456789/5312

Joseph, M., Moonsammy, S., Davis, H., Warner, D., Adams, A., & Oyedotun, T. D. T. (2023). Modelling climate variabilities and global rice production: A panel regression and time series analysis. *Heliyon*, *9*(4). https://doi.org/10.1016/j.heliyon.2023.e15480

Joshi, H. P., Techato, K., Phoungthong, K., & Panthee, K. R. (2023). Determinants of rice production in Nepal. *Sarhad Journal of Agriculture, 39*(3): 616-624. https://dx.doi.org/10.17582/journal.sja/2023/39.3.616.624

Khan, A. A., & Jadaun, K. K. (2023). Estimating the potential effect of climate change on rice yield in India by considering the combined effects of temperature and rainfall. *Bhartiya Krishi Anusandhan Patrika*, *38*(3), 284-289. http://dx.doi.org/10.18805/BKAP649

Kumar, N.K. (2024). An In-Depth Analysis of Macroeconomic Factors Influencing Nepal's Economic Growth. NPRC Journal of Multidisciplinary Research, 1(6), 13-22. https://doi.org/10.3126/nprcjmr.v1i6.71739

Mahmood, N., Ahmad, B., Hassan, S., & Bakhsh, K. (2012). Impact of temperature ADN precipitation on rice productivity in rice-wheat cropping system of Punjab province. *The Journal of Animal & Plant Sciences, 22*(4), 993-997.

Mainuddin, M., Peña-Arancibia, J. L., Karim, F., Hasan, M. M., Mojid, M. A., & Kirby, J. M. (2022). Long-term spatio-temporal variability and trends in rainfall and temperature extremes and their potential risk to rice production in Bangladesh. *PLOS Climate*, *1*(3), e0000009. https://doi.org/10.1371/journal.pclm.0000009

Mohapatra, S., Wen, L., Sharp, B., & Sahoo, D. (2024). Unveiling the spatial dynamics of climate impact on rice yield in India. *Economic Analysis and Policy*, *83*, 922-945. https://doi.org/10.1016/j.eap.2024.07.021

Pesaran, M. H., & Shin, Y. (1995). An autoregressive distributed lag modeling approach to cointegration analysis 9514, 371-413. Cambridge, UK: Department of Applied Economics, University of Cambridge. https://doi.org/10.1017/CBO9781139052221.011

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics, 16*(3), 289-326. https://doi.org/10.1002/jae.616

Poudel, O. (2022). Impacts of foreign direct investment on economic growth of Nepal: A Johansen co-integration analysis. *Journal of Balkumari College, 11*(1), 50-62. https://doi.org/10.3126/jbkc.v11i1.53023

Poudel, O. (2023). Relationship between defense expenditure and economic growth in Nepal. *Unity Journal, 4*(1), 208–226. https://doi.org/10.3126/unityj.v4i01.52242

Poudel, O., Acharya, P., Chandra Kafle, S., & Adhikari, B. P. (2024a). Balancing progress and preservation: The complex interplay of economic growth and forest conservation in Nepal's carbon dioxide emissions. *Discrete Dynamics in Nature and Society*, *2024*(1), 7562668. https://doi.org/10.1155/2024/7562668

Poudel, O., Kharel, K. R., Acharya, P., & Upadhyaya, Y. M. (2024). Insights into livestock-induced co$_2$ emissions: Nepal's environmental challenges. *Interdisciplinary Journal of Management and Social Sciences*, *5*(2), 134-151. https://doi.org/10.3126/ijmss.v5i2.69452

Poudel, O., Kharel, K. R., Acharya, P., Simkhada, D., & Kafle, S. C. (2024b). ARIMA modeling and forecasting of national consumer price index in Nepal. *Interdisciplinary Journal of Management and Social Sciences,* *5*(1), 105-118. https://doi.org/10.3126/ijmss.v5i1.62666

Rahman, M. A., Kang, S., Nagabhatla, N., & Macnee, R. (2017). Impacts of temperature and rainfall variation on rice productivity in major ecosystems of Bangladesh. *Agriculture & Food Security*, *6*, 1-11. https://doi.org/10.1186/s40066-017-0089-5

Ratnayake, S. S., Reid, M., Larder, N., Kadupitiya, H. K., Hunter, D., Dharmasena, P. B., Kumar, L., Kogo, B., Herath, K., & Kariyawasam, C. S. (2022). Impact of climate change on paddy farming in the village tank cascade systems of Sri Lanka. *Sustainability*, *15*(12), 9271. https://doi.org/10.3390/su15129271

Rimi, R. H., Rahman, S. H., Karmakar, S., & Hussain, S. G. (2009). Trend analysis of climate change and investigation on its probable impacts on rice production at Satkhira, Bangladesh. *Pakistan Journal of Meteorology*, *6*(11), 37-50.

Sarker, M. A. R., Alam, K., & Gow, J. (2012). Exploring the relationship between climate change and rice yield in Bangladesh: An analysis of time series data. *Agricultural Systems*, *112*, 11-16. https://doi.org/10.1016/j.agsy.2012.06.004

Thapa, N., & Chand, J. (2024). Nexus of climate change, irrigation requirement and water balance for paddy production in Chandra Canal Irrigation System, Nepal. *Paddy and Water Environment*, 1-16. https://doi.org/10.1007/s10333-024-01006-3

Thapa, R., & Dhakal, S. C. (2024). Climate change perception and adaptation strategies of rice seed growers in Chitwan district, Nepal. *Farming System*, *2*(3), 100095. https://doi.org/10.1016/j.farsys.2024.100095

Upendram, S., Regmi, H. P., Cho, S. H., Mingie, J. C., & Clark, C. D. (2023). Factors affecting adoption intensity of climate change adaptation practices: A case of smallholder rice producers in Chitwan, Nepal. *Frontiers in Sustainable Food Systems*, *6*, 1016404. https://doi.org/10.3389/fsufs.2022.1016404

World Bank. (2024). Climate Change Knowledge Portal: Nepal – Climate data historical. Retrieved December 10, 2024, from https://climateknowledgeportal.worldbank.org/country/nepal/climate-data-historical

Zhang, Q., Akhtar, R., Saif, A. N. M., Akhter, H., Hossan, D., Alam, S. A., & Bari, M. F. (2023). The symmetric and asymmetric effects of climate change on rice productivity in Malaysia. *Heliyon*, *9*(5). https://doi.org/10.1016/j.heliyon.2023.e16118