IMPACT OF SEASONAL RAINFALL AND TEMPERATURE VARIABILITY ON PADDY PRODUCTION IN ARGHAKHANCHI DISTRICT, NEPAL: EVIDENCE FROM THE ARDL APPROACH

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Abstract. Climate is an important factor in the agricultural sector, and changes in it may significantly impact crop production. Paddy (*Oryza sativa*) ranks first in Nepal in terms of both cultivated areas and production, and is regarded as one of the most important and primary staple foods in the country. This study analyses the impact of climatic variables such as seasonal precipitation (pre-monsoon, monsoon, post-monsoon) and temperature (maximum and minimum) on paddy production using the Autoregressive Distributed Lag (ARDL) model with time-series quantitative data from 1990 to 2023 in Nepal's mid-hill region. The results showed a long-term positive relationship between post-monsoon precipitation and paddy output, whereas pre-monsoon precipitation was found to have a significantly negative impact. Similarly, extreme temperatures and annual precipitation have been demonstrated to be statistically irrelevant in the long run. Lagged high temperatures and substantial post-monsoon rainfall reduced yields in the short term, demonstrating the adverse impacts of heat stress and late-season rainfall on rice production. The model has significant explanatory power (adjusted $R^2 = 0.9646$) and stability, with diagnostic tests revealing no autocorrelation, heteroscedasticity, or model misspecification. The considerable error correction term (-0.7005) indicates that almost 70% of departures from long-run equilibrium are corrected annually, implying a resilient yet climate-sensitive agricultural system. The results highlight the importance of implementing climate-smart agricultural policies that focus on seasonal climate trends, effective water management strategies, and resilient farming techniques to protect food security in Nepal's susceptible mid-hill areas.
Keywords: *climate variability, crop-climate interaction, agricultural productivity, mid-hill agroecosystem, ARDL model*

Introduction

The effects of climate change are felt across the world. Human and environmental systems are expected to be at risk from the ongoing and upcoming effects of significant climate change (IPCC, 2014b; Karki et al., 2020). According to the Intergovernmental Panel on Climate Change (IPCC) in its Sixth Assessment Report, the global average temperature rose by 1.10°C during the decade from 2011 to 2020, and this increase is expected to continue, with projections indicating a rise of approximately 1.3°C to 5.7°C by the end of the century, depending on whether low- or high-emission scenarios unfold (Masson et al., 2021). Furthermore, IPCC reports in 2021 revealed that South Asia is particularly vulnerable

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to these temperature increases, which are expected to significantly impact critical sectors including agriculture, land use, energy, biodiversity, public health, and water resources.

Nepal is primarily a mountainous country that is part of the HKH (Hindu Kush Himalaya) region in South Asia, where 43% of the land is made up of hills, of which 40% are under cultivation, a process that is mostly carried out by smallholder farmers (Abington, 1992; Paudel et al., 2011; Bhusal et al., 2025). By 2050, average temperatures in the HKH region are projected to rise by over 2°C, with even greater warming expected at higher elevations, which may cause nearly one-third of the region's glaciers to melt by 2100; however, water supply and ecosystem stability will suffer greatly from this (Sharma et al., 2019; Bhusal et al., 2022).

Climate monitoring records show that by 2060, Nepal's annual rainfall will decrease by 10% to 20%, while the average annual temperature would increase by 0.06°C (Amponin and Evans, 2016). In a similar vein, forecasts show that by 2030, temperatures will rise by 0.5°C to 2°C and precipitation will vary by -34% to +22% due to climate change (Karki and Gurung, 2012). The average annual temperature is expected to increase by 1.2°C by 2030, 1.7°C by 2050, and 3°C by 2100, according to the Nepal Climate Vulnerability Study Team (NCVST, 2009) and the Organization for Economic Cooperation and Development (OECD, 2003) (Thapa et al., 2015). Therefore, the projection on the changes of climate variables shows a serious threat in the country's agricultural activities.

Additionally, according to the Climate Change Vulnerability Index (CCVI), Nepal ranks fourth in South Asia and is among the world's most vulnerable nations. This is because the country is mostly agricultural, with more than 66% of the population and almost 80% of households (3.4 million) engaged in agricultural activities and their main source of income is from natural resources. It is also states that the agriculture contributes up around 27% of the country's GDP and climate has significant impacts on agricultural output (MoF, 2019; MoFE, 2021).

The country's entire cultivated land area is 3,343,135 ha, representing 21% of its total land area and 1,447,789 ha are dedicated to paddy agriculture (MoALD, 2024). Similarly, the hill region accounts for 24% of regional rice output, whereas the mountain region contributes only 3%. The Terai region dominates, accounting for 73% of the country's total paddy yield (Gauchan and Pandey, 2011).

Despite the critical significance of the issue and the growing threat to food security, insufficient is known about the degree of climate change and its effects on cereal crops in Nepal's hill agricultural ecological zone. Existing research indicates major changes in temperature trends across much of the country. In particular, lower elevation areas exhibit increasing trends in both seasonal and annual minimum temperatures, whereas higher elevations demonstrate declining trends, highlighting the spatial variability of climate impacts within the region. Every season, except for the Terai in winter and pre-monsoon, and the Siwaliks in winter, shows a notable increase in the annual maximum temperature (GoN, 2017; Dawadi et al., 2022). Studies that have used data from high elevation stations and mountains have also shown the warming trend, which may impact the crop production (Kattel et al., 2013; Thakuri et al., 2019; Dawadi et al., 2020). Therefore, in order to identify and develop sustainable adaptation options for current and future climate risk, empirical research on climate change is required to quantify the regional impacts.

In Nepal's hill and high-hill regions, the three climatic seasons- pre-monsoon (March-May), monsoon (Jun-August), and post-monsoon (September-November)-virtually coincide with the growing seasons of paddy crop and the climate has always been important for its cultivation (Paudyal, 2001; Dawadi and Sah, 2012). More than 80% of

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the annual rainfall still occurs during the monsoon season, providing significant agricultural value to many regions of the nation (Salerno et al., 2015; Hamal et al., 2020; Perry et al., 2020; Sharma et al., 2020). Rice is one of the most important and considered a primary staple food because up to 90% of Nepalese people consume it (Sapkota and Sapkota, 2019), which accounts for more than half of the calories consumed in the country (Khanal et al., 2018; Gadal et al., 2019).

Previous studies conducted in Arghakhanchi district have primarily focused on farmers' perceptions of insect pests and their management (Parajuli et al., 2023), adoption of good agricultural practices among vegetable growers (Nepal et al., 2023), and farmers' perception and adaptation strategies toward climate change (Poudel et al., 2020). Despite their contributions, these studies are predominantly perception and practice-oriented, and lack quantitative assessments based on long-term observational datasets. As a result, the dynamic linkages between climatic variability and paddy production at the district scale remain insufficiently understood. To address this gap, the present study is the first to utilize long-term climatic and paddy production data (1990–2023) and applies an ARDL (Autoregressive Distributed Lag) model to estimate both long-run equilibrium relationships and short-run adjustment dynamics between climatic variables and paddy production, thereby offering robust, data-driven evidence on climate–crop interactions in the mid-hill agro-ecological context of Nepal.

The primary objective of this study is to analyze long-term trends in key climatic variables and paddy production over the period 1990–2023, and to examine the existence of both long-run and short-run relationships between climatic variables and paddy production within Nepal's mid-hill agro-ecological zone (Arghakhanchi district). Specifically, the study seeks to address the following research questions: (1) what is the nature and direction of the relationship between climatic variables and paddy production? And (2) how do short-term fluctuations and long-term changes in climatic conditions within the study area influence variations in paddy production?

Materials and methods

Study area

The study was carried out in Nepal's Arghakhanchi district (shown in *Fig. 1A*), which is in latitudes 27°55'0" (N) and longitudes 83°4'60" (E), and elevation above sea level ranges from 305 to 2515 m. The total area of this district is 1193 km^2, bordered to the north by Gulmi district, to the east by Palpa district, to the south by Kapilvastu district, and to the west by Pyuthan district (Government of Nepal, 2021). There are four separate climatic zones in this district: temperate (2000 to 3000 m, 0.2%), subtropical (1000 to 2000 m, 49.1%), upper tropical (300 to 1000 m, 50.50%), and lower tropical (below 300 m, 0.2%). 68% of the area is covered by mountains, with the remaining portion being other land is in Siwalik Hills. *Figure 1B* shows the land cover data of Argakanchi district using freely available 30 m resolution Landsat satellite images for the year 2022 (Path and row: 142/041, 143/041, https://earthexplorer.usgs.gov/). Similarly, *Figure 1C* illustrates the district's elevation, derived from the Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM).

With 48,465 households and a total population of 177,086 people, this district has a population density of 148 km^2. The total land coverage by Arghakhanchi district is 119,300 ha, which is equivalent to 1193 km^2. The proportion of land use types in this district is characterized by 34.65% (41,327 ha) cultivated land, 57% forested land, 4.8%

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river and ponds land, and 3.55% residential and other land (MoALD, 2025). It has been found that 94.4% of the people in this area worked in agriculture, with the primary cereal crops farmed being paddy, maize, barley, wheat and mustard (Government of Nepal, 2021). Therefore, when choosing the study location, the district's susceptibility to climate change was considered.

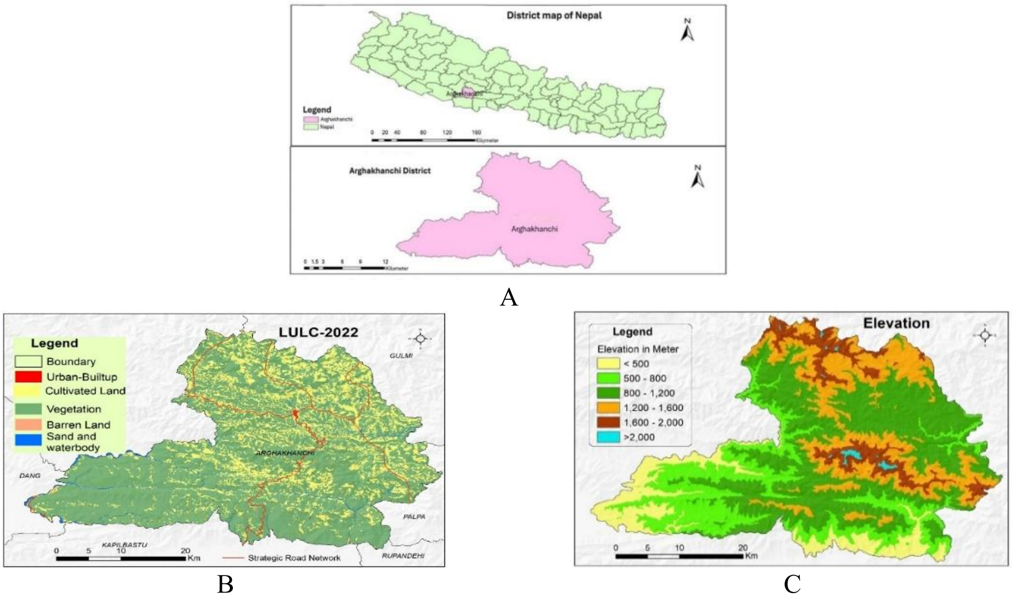

Figure 1. *Study location map (A), land use land cover map of the study area (2022) (B), and elevation map of the study area (C)*

Data sources

Thirty-four years of quantitative historical climate data (1990–2023) from the Department of Hydrology and Meteorology in Kathmandu, Nepal were used in this study. Daily precipitation and temperature data were examined. There are 4 different meteorological substations in Arghakhanchi district, such as Khanchikot substation (station index 0715), Nepaney substation (station index 0730), Sidhara substation (station index 0735), and Sandhikharkha substation (station index 0750), where Khanchikot substation was stablished in 1975, which equipped with an automatic weather station system to record real-time data. Other meteorological substations are recently stablished and not well equipped to record climatic data properly. Therefore, only Khanchikot substation was selected for 34 years of long-term climatic (rainfall and temperature) data for this study. In addition, the Arghakhanchi district's yearly paddy output figures from 1990 to 2023 were obtained from the Ministry of Agriculture and Livestock Development in Kathmandu, Nepal, and are expressed in metric units.

Econometric framework and estimation procedure

The study utilizes the Autoregressive Distributed Lag (ARDL) modeling framework, suitable for variables with integration orders I(0) and I(1), but not I(2) or when the dependent variable is stationarity at level (I(0)) with a deterministic trend, and the independent variables are stationarity at level (I(0)), following Model 4 of Pesaran et al. (2001). A variable is said to be integrated of order zero, I(0), when it is stationary in

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levels, meaning its statistical properties such as mean and variance remain constant over time. A variable is I(1) when it becomes stationary only after first differencing. Excel and EViews 12 was used for data analysis purpose. The econometric procedure includes descriptive statistics, trend analysis and the Jarque-Bera normality test, the Augmented Dicky Fuller (ADF) unit root test, optimal lag selection via the Akaike Information Criterion (AIC), the Final Prediction Error (FPE), the Hannan Quinn (HQ) information criterion, and the Schwarz Criterion (SC) criteria, the ARDL bounds test for cointegration, estimation of long-run coefficients, and short-run dynamics through the Error Correction Model (ECM). Additional steps consist of residual diagnostics for serial correlation, heteroscedasticity, normality, functional form, and stability tests using Cumulative SUM (CUSUM) and Cumulative SUM of Squares (CUSUMSQ).

Model specification

The study evaluated two models for Paddy production (PP): a linear model and a Log-linear Paddy Production (LNPP) model. The linear model reflects absolute production changes, while the log-linear model offers elasticity interpretations and addresses heteroscedasticity issues in agricultural data. Ultimately, the log-linear specification was chosen for ARDL estimation based on diagnostics and theoretical factors.

The analytical framework of this study employs ARDL (Autoregressive Distributed Lag) model, which is well-suited to understand the dynamic relationships between multiple independent variables such as rainfall (pre-monsoon, monsoon, post-monsoon), and temperature (maximum and minimum), and a dependent variable i.e., paddy production of mid-hill agro-ecological region (Arghakhanchi district) of Nepal. The following level (linear) model, which uses paddy production in levels (PP) is illustrated below and provides an overview of the study.

$$PP = \beta_0 + \beta_1 \text{ PostM} + \beta_2 \text{ PreM} + \beta_3 \text{ M} + \beta_4 \text{ Tmax} + \beta_5 \text{ Tmin} + \epsilon_t \qquad \text{(Eq.1)}$$

Agricultural output data often exhibit heteroskedasticity and scale dependency. To obtain elasticity coefficients and mitigate the influence of outliers, the variables are transformed into logarithmic form. In the log-linear (semi-log) specification, the function is expressed as:

$$LNPP = \beta_0 + \beta_1 \text{ PostM} + \beta_2 \text{ PreM} + \beta_3 \text{ M} + \beta_4 \text{ Tmax} + \beta_5 \text{ Tmin} + \epsilon_t \qquad \text{(Eq.2)}$$

In this case LNPP is stationarity at trend only at level (I(0)), and, PreM, M, PostM, Tmax and Tmin are stationary at level (I(0)) for both intercept and trend which shows the ARDL (3,2,2,2,3,1) with deterministic trend (Dickey and Fuller, 1979; Pesaran et al., 2001; Devkota and Paija, 2020; Bista et al., 2024).

$$\begin{aligned} LNPP_t = \alpha_0 + \alpha_1(trend(t)) + \sum_{i=1}^{3} \varphi_i LNPP_{t-i} + \sum_{j=0}^{2} \beta_{1,j} PostM_{t-i} \\ + \sum_{j=0}^{2} \beta_{2,j} PreM_{t-j} + \sum_{j=0}^{2} \beta_{3,j} M_{t-j} + \sum_{j=0}^{2} \beta_{4,j} Tmax_{t-j} \\ + \sum_{j=0}^{1} \beta_{5,j} Tmin_{t-j} + \epsilon_t \end{aligned} \qquad \text{(Eq.3)}$$

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where, LNPP = Natural logarithm of annual Paddy Production, PostM = Post-monsoon (in mm), PreM = Pre-monsoon, M = Monsoon, Tmax = Maximum temperature, Tmin = Minimum temperature $\epsilon_{t,}$= error, $\alpha_0 \ = intercept\ and\ \alpha_1$ = coefficient of trend.

Results

Descriptive analysis

This study applied both descriptive and exploratory research designs to analyze the effects of climate-related variables on paddy production. Secondary data from 1990 to 2023 were used. The main dependent variable was LNPP (Log-linear Paddy Production), while independent variables included Pre-monsoon (PreM), monsoon (M), Post-monsoon (PostM), and temperature variables maximum temperature (Tmax) and minimum temperature (Tmin). Data were sourced from national statistical records and meteorological datasets.

As confirmed by non-significant Jarque-Bera p-values ($p > 0.05$), the descriptive statistics verify that all important variables such as; LNPP, seasonal rainfall indices (PreM, M, PostM) are measured in millimeters representing total precipitation during, and temperature extremes (Tmax, Tmin) measured in degree Celsius (°C), have approximately normal distributions (shown in *Table 1*). This allows the application of common econometric techniques that assume stability.

Table 1. *Descriptive statistics and normality test for climatic and environmental variables*

Variables	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera p-value	Normality
LNPP (natural log of annual paddy production, metric tons)	9.72	0.322	-0.36	2.25	0.463	p > 0.05
Post monsoon (PostM) (in milimeters)	283.9	126.3	0.68	3.48	0.232	p > 0.05
Pre monsoon (PreM) (in milimeters)	195.51	86.66	0.28	3.02	0.800	p > 0.05
Monsoon (M) (in milimeters)	1168.37	279.19	0.57	3.65	0.296	p > 0.05
Temperature maximum (Tmax) (in°C)	20.76	0.59	-0.31	2.37	0.569	p > 0.05
Temperature minimum (Tmin) (in°C)	12.66	0.49	-0.15	3.94	0.500	p > 0.05

Trend analysis of climatic variables and paddy production

In this study, temperature and rainfall are considered as climatic variables, and paddy production is as a dependent variable.

Variation of rainfall

Over a period of 34 years (from 1990 to 2023), the pre-monsoon rainfall in studied area exhibits significant inter-annual variability. Linear trend analysis exhibits overall pre-monsoon rainfall patterns are rising at a rate of 2.89 mm per year (*Fig. 2A*). With a total of 421.6 mm, the highest pre-monsoon rainfall was recorded in 2021. This was followed by 311.3 mm in 2022, 289.23 mm in 2023, and 288.6 mm in 2018, suggesting an increase in precipitation over the previous ten years. However, 1999 was the driest

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pre-monsoon year, with just 13.6 mm of rainfall. Significantly lower totals were recorded in 1996 (64.1 mm) and 1991 (106.4 mm).

Similarly, the study reflects a minor increasing tendency in monsoonal rainfall at a rate of 0.82 mm per year (*Fig. 2B*). Monsoon rainfall picked in 2013 (1841.2 mm) and 1998 (1836.2 mm), with 1996 (1715.5 mm) and 2008 (1470.7 mm) following closely behand. On the other hand, 2002 saw the lowest monsoon rainfall over the period with only 563.2 mm, indicating a possible drought. Intense monsoonal rains occurred in several years in the 1990s and early 2000s, but subsequent years like 2021 (1403.9 mm) and 2022 (1363.6 mm) also show notable monsoon activity, indicating that monsoon rainfall continues to dominate the region's hydroclimate.

Furthermore, post-monsoon precipitation demonstrates considerable annual variability, while the total amounts are inferior to those observed during the rainy season. However, linear trend analysis shows that the total post-monsoon rainfall is increasing at a rate of 1.14 mm per year (*Fig. 2C*). Extreme post-monsoon rainfall was recorded in 1993 (627.88 mm), 2021 (560.7 mm), and 2007 (482.8 mm), demonstrating that severe rainfall events can occur beyond the regular monsoon window. In comparison, the driest following the monsoon year was 2015, which received only 67.5 mm of rain, and some other notable drought years are 2006 (113.1 mm) and 2018 (107.1 mm).

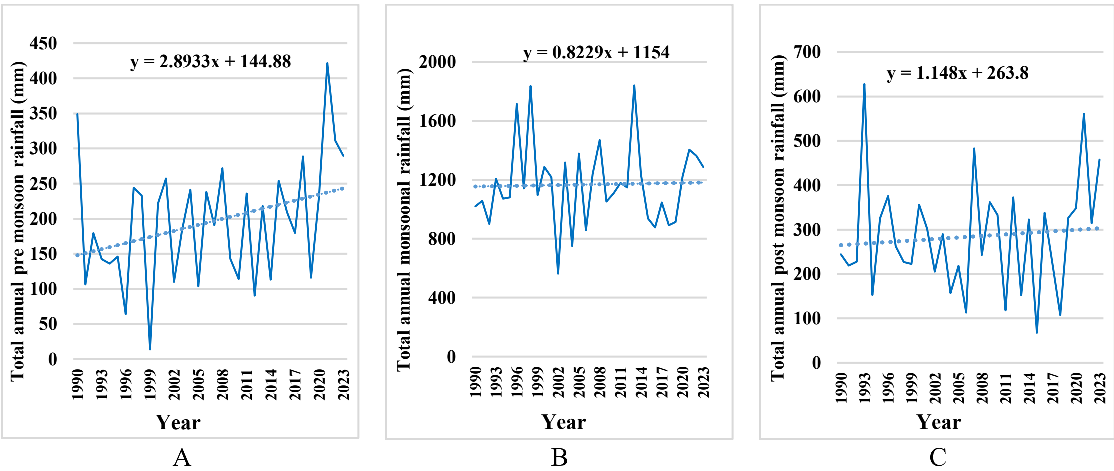

Figure 2. *Total annual pre monsoon rainfall (A), total annual monsoonal rainfall (B), and total annual post monsoon rainfall (C) in the Arghakhanchi District from 1990 to 2023*

The overall results suggest very varying and growing patterns over all three rainfall seasons: pre-monsoon, monsoon, and post-monsoon.

Variation of temperature

Figure 3 has demonstrated the trend analysis of average annual maximum, minimum, and average temperature in Arghakhanchi district during the period of 1990 to 2023.

Over the past three decades, the mean annual maximum temperature in study area has gradually increased by 0.40°C per year. Further, maximum temperature rose steadily from a comparatively constant 19.8°C in the early 1990s to 21.7°C in several years (2009, 2010, and 2023). There was a noticeable shift in the early 2000s, with temperature rises surpassing 21°C in several years, including 2000, 2002, and 2006. Overall, a gradual

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intensification of heat during the warmest months is suggested by the long-term rise in maximum temperatures.

Despite having more inter-annual variability than the maximum temperature, the mean annual minimum temperature likewise exhibited an overall upward trend at a rate of 0.031°C per annum (*Fig. 4*). Likewise, the minimum temperature began to fluctuate around 12.5°C in 1990 and continued to do so until the mid-2000s, when there was a discernible increase. 2009 (13.9°C) and 2010 (13.6°C) had exceptionally high readings. A minimum temperature of 13.1°C is shown in the most recent data from 2023.

A consistent increase is also shown by the annual average temperature, which is determined by averaging the yearly maximum and minimum temperatures, The trend analysis indicates a significant increasing trend at a rate of 0.031°C per year (*Fig. 4*). In 1990, it was concerning 16.2°C, stayed mostly constant through the early 1990s, and reached its highest point in the series in 2009 at 17.8°C. A shift toward a warmer climate regime was confirmed in a number of other recent years, including 2010, 2016, and 2023, when average temperatures exceeded 17°C. A warming of between 0.8–1.0°C over the study period is evident when comparing the average temperature from the 1990s (nearly 16.2°C) to the 2010s and early 2020s (often exceeding 17°C).

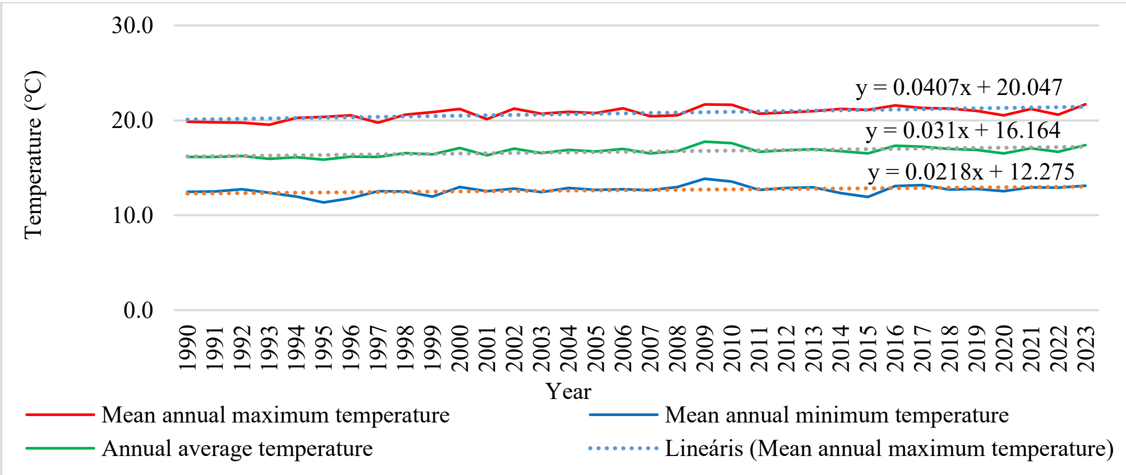

Figure 3. *Mean annual maximum, minimum and average temperature in Arghakhanchi District from 1990 to 2023*

Overall, the Arghakhanchi district's temperature data from 1990 to 2023 point to a distinct warming trend, marked by rising maximum and minimum annual temperatures. The average temperature also has risen by about 1°C over the past three decades.

Trend of paddy production

Paddy production in Arghakhanchi District demonstrated a sustained upward trend over the period 1990–2023, increasing at an average rate of 462.99 metric tons per year (*Fig. 4*). Trend analysis showed with multiple distinct growth, stability, and sometimes fluctuation phases. Beginning at 8680 metric tons in 1990 and progressively rising to 13,961 metric tons by 1994, production was comparatively low and inconsistent in the early 1990s. Again, Production increased steadily between the mid-1990s and the early 2000s, reaching 17,010 metric tons in 2002. From 2003 to 2008, there was a plateau, with output ranging from 13,900 to 14,500 metric tons. Between 2009 and 2014, there was a sharp increase in

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production, which peaked at a record 26,306 metric tons in 2014. But following this peak, the output gradually decreased, dropping to 21,219 metric tons in 2021 before slightly increasing in the years that followed, reaching 22,266 metric tons by 2023.

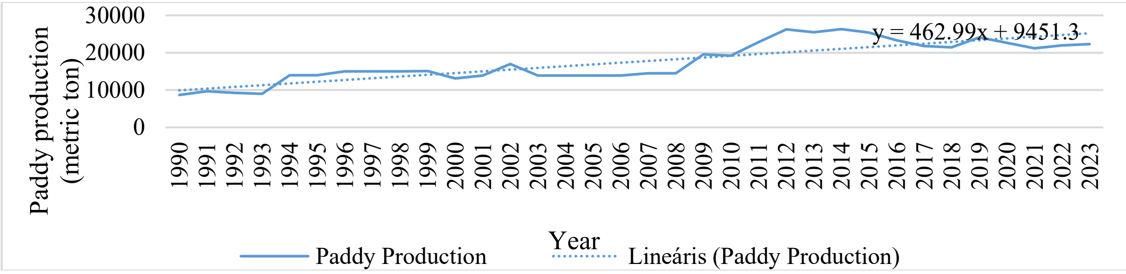

Figure 4*. Production of paddy in Arghakhanchi District from 1990 to 2023*

Unit root test

ADF (Augmented Dicky Fuller) test results from the *Table 2* shows LNPP is stationarity at trend only at level (I(0)), and PostM, PreM, M, Tmax and Tmin are stationary at level (I(0)) for both intercept and trend which shows the ARDL with deterministic trend (Dickey and Fuller, 1979; Pesaran et al., 2001).

Table 2. *Result of unit root test (augmented Dickey-Fuller test) for climatic and environmental variables*

Variable	Intercept (constant)	Intercept and trend	Conclusion
LNPP	0.3052	0.014*	Stationary at constant and trend only I(0)
Post-monsoon (PostM)	0.000*	0.000*	Stationary for both, I(0)
Pre-monsoon (PreM)	0.000*	0.000*	Stationary for both, I(0)
Monsoon (M)	0.000*	0.000*	Stationary for both, I(0)
Temperature maximum (Tmax)	0.024*	0.002*	Stationary for both, I(0)
Temperature minimum (Tmin)	0.0272*	0.0348*	Stationary for both, I(0)

*p value < 0.05

The result also shows that post-monsoon precipitation, Pre-monsoon precipitation, Monsoon precipitation, maximum temperature, and minimum temperature are stationary under both specifications, indicating a deterministic trend at level I(0).

Lag length selection

The optimal lag structure was identified lag order 3 as optimal using the Akaike Information Criterion (AIC), which selected the ARDL (3, 2, 2, 2, 3, 1) model as the most parsimonious. This model included three lag of the dependent variable (LNPP) and up to three lags of the explanatory variables: post-monsoon (PostM), pre-monsoon (PreM), monsoon (M), Tmax, and Tmin. The model's adjusted R-squared was 0.9346, indicating that over 93% of the variability in LNPP was explained by the regressors. The overall F-statistic was highly significant ($F = 24.80306$, $p < 0.05$), affirming the joint significance of the model. Depending on the parameters applied, the lag order selection test results indicate differing ideal lag lengths. As shown in *Table 3,* the minimal values for the FPE

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(Final Prediction Error), AIC (Akaike Information Criterion), and HQ (Hannan-Quinn) criterion for this lag show that a lag duration of 3 is ideal.

Table 3. *VAR lag length selection criteria*

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-627.3615	NA	2.25e + 10	40.86203	41.13958*	40.95251
1	-574.2827	82.18657*	7.82e + 09	39.76017	41.70300	40.39349
2	-536.6168	43.74109	9.33e + 09	39.65269	43.26079	40.82884
3	-473.4029	48.93977	3.87e + 09*	37.89696*	43.17033	39.61595*

Adequacy and fit of the ARDL model

The long and short-term correlations between paddy production (LNPP) and meteorological factors were investigated using the ARDL bounds testing method of Pesaran et al. (2001). ADF tests revealed mixed integration orders: all other variables were stationary at level with a constant, while LNPP was trend stationary. To account for the trend-stationarity of LNPP, Model 4 (unrestricted intercept, restricted trend) was used. ARDL (3, 2, 2, 2, 3, 1) was the best lag structure determined using the Akaike Information Criterion. With an $R^2 = 0.9870$ and an adjusted $R^2 = 0.9646$, the ARDL model exhibits exceptional explanatory power, indicating that it accounts for more than 96% of the variance in LNPP. Overall model significance is confirmed by the F-statistic (44.08, $p < 0.05$). There is no significant autocorrelation, as indicated by the Durbin-Watson statistic (1.82), which is near to 2 (Durbin and Watson, 1992).

Table 4 shown that the LNPP (−1), LNPP (−2), and LNPP (−3) denote the first, second, and third lags of the dependent variable, representing the effect of past paddy production levels on current production. Similarly, PreM (-1), PreM (-2), M(-1), M(-2), PostM (−1), PostM (-2), Tmin (-1), Tmax (-1), Tmax (-2) and Tmax (−3) lagged terms represent rainfall or temperature values from previous years, included to capture delayed climatic effects on production growth of paddy.

Table 4. *Estimated coefficients of ARDL model*

Variable	Coefficient	Standard error	t-Statistic	P-value
LNPP (-1)	0.341	0.15	2.281	0.043*
LNPP (-2)	0.196	0.171	1.149	0.275
LNPP (-3)	-0.238	0.136	-1.75	0.108
PostM	-0.0002	0.0001	-1.459	0.173
PostM (-1)	0.0007	0.0001	4.892	0.001*
PostM (-2)	0.0005	0.0001	3.926	0.002*
PreM	-0.0014	0.0002	-6.978	0.000*
PreM (-1)	-0.00075	0.0002	-3.195	0.009*
PreM (-2)	-0.00091	0.0002	-4.522	0.001*
M	-0.0000637	0.000053	-1.202	0.255
M (-1)	0.0000399	0.000043	0.927	0.374
M (-2)	0.0001	0.0000501	2.613	0.024*
Tmax	0.006	0.039	0.163	0.873
Tmax (-1)	-0.058	0.032	-1.836	0.094
Tmax (-2)	0.049	0.031	1.566	0.146
Tmax (-3)	0.08	0.037	2.199	0.05*
Tmin	-0.012	0.037	-0.337	0.743
Tmin (-1)	-0.04	0.029	-1.376	0.196
Constant I	5.598	2.01	2.784	0.018*
Trend (@trend)	0.027	0.006	4.685	0.001*

R-squared = 0.9870, adjusted R-squared = 0.9646, F statistic = 44.0802 ($p = 0.000 < 0.05$), DW = 1.8176, $^*p < 0.05$

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Long run bound test

The bounds test for cointegration strongly supports a long-run equilibrium relationship among the variables, with the F-statistic (10.48) exceeding the critical upper bounds at 1%, 5%, and 10% significance levels (shown in *Table 5*).

Table 5. *ARDL bound test results*

Significance level	i(0) bound	I(1) bound	F
10%	3.097	4.118	10.48
5%	3.715	4.878	
1%	5.205	6.64	

As shown in *Table 6,* the long-run ARDL estimates indicate that LNPP exhibits strong self-correcting behavior, as shown by the negative and significant lagged dependent variable coefficient (– 0.7005, $p < 0.05$). This suggests that long-term equilibrium deviations are gradually corrected, with an annual adjustment of about 70% of the disequilibrium.

Table 6. *Estimated long-run coefficients from the ARDL model (dependent variable: LNPP)*

Variables	Coefficient	p-Value	Result
LNPP (-1)	-0.7005	0.0002*	Significant, Strong self-correcting behavior, - 2917 -reusch. 70% adjusted toward equilibrium annually
PostM (-1)	0.0010	0.0092*	Significant, positive long run effect; higher post-monsoon rainfall increases LNPP
PreM (-1)	-0.0031	0.0001*	Significant, Negative long-run effect, excess pre-monsoon rainfall reduces LNPP
M (-1)	0.0001	0.1973	Non-significant
Tmax (-1)	0.0774	0.4275	Non-significant
Tmin (-1)	-0.0521	0.2294	Non-significant
@trend	0.0273	0.0007*	Significant, positive deterministic trend; upward shift in LNPP overtime
Constant	5.595	0.0178*	Significant, Baseline level of LNPP

*$p < 0.05$

The long-run ARDL estimates indicate that LNPP exhibits strong self-correcting behavior, as shown by the negative and significant lagged dependent variable coefficient (– 0.7005, $p < 0.05$). This suggests that long-term equilibrium deviations are gradually corrected, with an annual adjustment of about 70% of the disequilibrium.

The importance of water supplies during the stages of grain filling and ripening is highlighted by the beneficial and considerable influence of post-monsoon rainfall on LNPP. On the other hand, there is a strong and unfavorable long-term correlation between pre-monsoon rainfall and the risk of planting difficulties or seedling destruction. The significant positive trend term indicates that LNPP rose consistently over the course of study, presumably because of better crop management, advantageous agricultural policies, and advances in technology. Likewise, the non-existence of statistically significant long-term

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effect from temperature (Tmax and Tmin) and monsoon rainfall (M) indicates that their influence is either temporary or overshadow by patterns of seasonal rainfall distribution.

Short run dynamics and error correction model (ECM)

A steady and quickly correcting cointegrating relationship with the climatic variables is confirmed by the error correction term (–0.7005, $p < 0.05$), which is negative and highly significant (shown in *Table 7a*). It shows that almost 70% of the departure from the long-run equilibrium in LNPP is corrected annually.

Table 7b shows that the paddy productivity is significantly impacted in the short term by variations in temperature and seasonal rainfall patterns. The significant negative effects of both contemporaneous and lagged post monsoon rainfall demonstrate how excessive rainfall late in the season can damage crops or delay harvesting. Pre-monsoon rainfall has two different effects: modest lagged rainfall encourages development in the following period, possibly by increasing soil moisture reserves, while heavy early-season rainfall reduces yields in the current period. The substantial negative effects of lagged maximum temperatures show that heat stress during critical growth phases reduces productivity. Despite their small effects, the lagged negative impact of monsoon rainfall emphasizes the significance of rainfall timing over total volume.

***Table 7a**. Short run error correction model*

Variable	Coefficient	Standard error	t-stat	p-value	Result
CointeQ	-0.7005	0.0658	-10.65	0.0000	p < 0.05, significant

***Table 7b.** Estimated short-run coefficients of the ARDL error correction model*

Variable	Coefficient	p-Value	Significance
D(LNPP(-1))	0.0419	0.6376	Not significant
D(LNPP(-2))	0.2382	0.0124**	Significant
D(PostM)	-0.000205	0.0040**	Significant
D(PostM(-1))	-0.000520	0.0000**	Highly significant
D(PreM)	-0.001434	0.0000**	Highly significant
D(PreM(-1))	0.000917	0.0000**	Highly significant
D(M)	-0.0000637	0.0826*	Marginal
D(M(-1))	-0.000131	0.0012**	Significant
D(Tmax(-1))	-0.1292	0.0000**	Highly significant
D(Tmin(-2))	-0.0803	0.0017**	Significant

**p < 0.05, *p < 0.10

Changes in seasonal rainfall patterns and temperature fluctuations have a significant short-term impact on paddy productivity. Excessive rainfall late in the season may harm crops or postpone harvesting, as evidenced by the substantial negative consequences of both contemporaneous and lagged post monsoon rainfall. Pre-monsoon rainfall has two distinct effects: although excessive early-season rainfall lowers yields during the current time, moderate lagged rainfall promotes growth during the subsequent period, may be through enhancing soil moisture reserves. Heat stress at vulnerable growth phases lowers production, as evidenced by the severe detrimental impacts of lagged

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maximum temperatures. The significance of rainfall timing over total volume is reinforced by the lagged negative impact of monsoon rainfall, despite their modest effects. All things considered, the short-term results emphasize the need for adaptive water and temperature management strategies to safeguard paddy production from seasonal climate shocks.

Residual diagnostic tests (serial correlation and heteroscedasticity)

The diagnostic tests validate the statistical soundness of the ARDL - 2919 -reus and the absence of severe specification issues. *Table 8(A)* shown the Breush-Goodfrey LM test, where the residuals show no signs of serial correlation (F-statistic p = 0.8197 > 0.05; Chi-square p = 0.3615 > 0.05), indicating that the error components are independent across time. Similarly, *Table 8(B)* shown the null hypothesis of homoscedasticity, which is not rejected by the Breusch-Pagan-Godfrey test (F-statistic p = 0.8339 > 0.05; Chi-square p = 0.6634 > 0.05), suggesting that residual variability is constant (Rutledge and Barros, 2002; Akpan and Moffat, 2018). Additionally, there are no indications of functional form misspecification according to the Ramsey RESET test (p = 0.5988 > 0.05), indicating that the model specification is suitable. All of these findings confirm that the estimated ARDL model Is dependable, well-specified, and appropriate for robust inference.

Table 8. *Breusch-Godfrey serial correlation LM test (A), and - 2919 -reusch-Pagan-Godfrey heteroscedasticity test (B)*

(A) Breusch-Godfrey serial correlation LM test			
F-statistic	0.307217	Prob. F(3,8)	0.8197
Obs*R-squared	3.202451	Prob. Chi-Square(3)	0.3615
(B) Heteroscedasticity test: Breusch-Pagan-Godfrey test			
F-statistic	0.610253	Prob. F(19,11)	0.8339
Obs*R-squared	15.90804	Prob. Chi-Square(19)	0.6634

For each of the explanatory variables in the ARDL model, multicollinearity was investigated using the centered Variance Inflation Factor (VIF). With the highest recorded value being 5.29, all centered VIF values were much below the widely recognized critical threshold of 10, suggesting the lack of significant multicollinearity (Gujarati and Porter, 2009). Despite the observation of large uncentered VIF values, this does not indicate problematic collinearity and is expected in models with numerous lagged variables (Pesaran and Shin, 1999). These results suggest that the coefficient estimates are reliable and that multicollinearity is unlikely to bias the statistical inference.

The Jarque–Bera normality test yields a probability value of 0.665 i.e., (p = 0.665 > 0.05) shown in *Figure 5,* failing to reject the null hypothesis of normally distributed residuals; combined with the near-zero mean, low skewness (–0.268), and kurtosis close to 3 (2.41), this confirms that the residuals satisfy the normality assumption required for valid statistical inference in the ARDL model.

Ramsey RESET test was also conducted to check for potential misspecification of the model's functional form. The null hypothesis of the test is that the model is correctly specified. The results, with an F-statistic of 0.295140 and an associated p-value of 0.5988, indicate that we fail to reject the null hypothesis at the 5% significance level. This

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suggests that the chosen functional form is appropriate and there is no evidence of a specification error in the model.

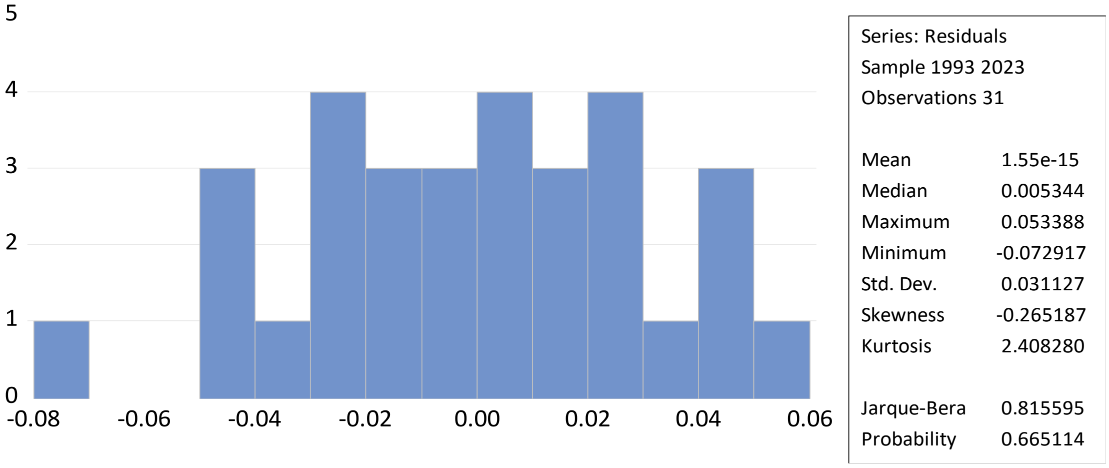

Figure 5. *Histogram and normality test of the residuals*

Stability test of the model

Although not graphically displayed, the mention of the CUSUM and CUSUMSQ (CUSUMS of squares) tests suggests that structural stability of the model was assessed. Assuming the plots remain within critical bounds, we infer that the model is dynamically stable over the sample period at 5% level of significance.

As shown in *Figure 6,* the CUSUM and CUSUMSQ tests for recursive residuals were used to evaluate the model's stability. The model's stability during the research period is confirmed by the results, which show that the plots of the CUSUM and CUSUMSQ both stay inside the essential boundary lines at the 5% significant level.

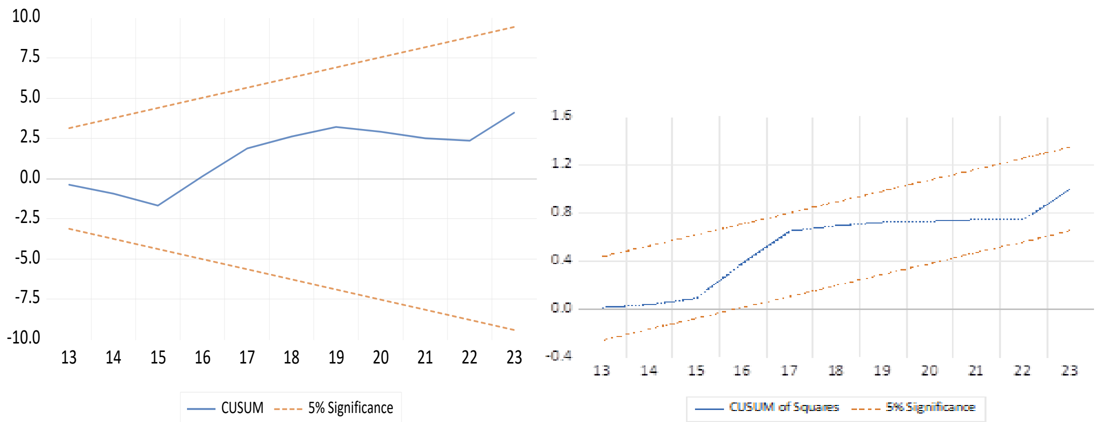

Figure 6. *CUSUM and CUSUM Square (CUSUMSQ) test for model stability*

Discussion

This study was employed in Arghakhanchi district in Nepal, which is mid-hill region geographically. The ARDL model is used to find out the impact of climatic variables such as temperature and seasonal precipitation on paddy production from 1990 until 2023. The findings include local actualities and an extensive theoretical idea, giving us

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many new clues regarding how climatic factors affect paddy production during this period.

As anticipated according to long-term ARDL estimates, LNPP went up with post-monsoon rainfall (PostM) while declining with pre-monsoon rainfall (PreM). This result aligns with some previous studies which show late-season rainfall enhanced soil moisture retention and reduced crop water stress during important phenological stages, thereby increasing yields (Wani et al., 2009; Lobell et al., 2011). Pre-monsoon rainfall, on the other hand, had a detrimental long-term effect on LNPP, a result consistent with some previous findings from Mall et al. (2006), Pathak et al. (2012), and Mishra and Lilhare (2016), which pointed out that high early-season rainfall could lead to waterlogging, poor germination, and insect outbreaks; all of these factors may reduce crop yield, thus emphasizing the role of total rainfall as well as its seasonal timing.

Interestingly, temperature variables (Tmax and Tmin) and Manson rainfall (M) are not found to be statistically significant over time, which may reflect the adoption of farming techniques to these changes or the fact that annual totals may obscure important intra-seasonal variability. This finding is supported by some previous studies in South Asia, where similar trends have been seen: rainfall dispersion is more important than annual totals (Aggarwal et al., 2010; IPCC, 2014a). Similarly, the study found that changes in rainfall before and after the monsoon have a significant short-term influence on paddy yield, with excessive rainfall around harvest time delaying or leading to loss of crops since productivity was found to be negatively correlated with lagged post-monsoon rainfall. These results are very much similar to the findings from the Indo-Gangetic plain; post-monsoon events sometimes coincide with harvest seasons, leading to output losses (Sharma et al., 2021).

Moreover, Tmax lagged was found to be significantly negative, reflecting that even short periods of heat stress can reduce paddy yield, likely because of increased evapotranspiration or reduced photosynthesis. The results have focused on the value of intra-annual climate variability and the importance of adapting to both long-term climatic trends and seasonal variability by farmers through selecting resistant seed types, planting schedules, enhanced irrigation and useing enough green manure.

The ARDL model is statistically well-specified, as indicated by the diagnostic tests (Breusch–Godfrey LM, Breusch–Pagan–Godfrey, Ramsey RESET); the functional form is correct, the model does not suffer from heteroskedasticity; there is no autocorrelation; the residual normality and multicollinearity tests (VIF < 10) confirm the stability of the calculated coefficients, and the CUSUM and CUSUMSQ graphs indicate the structural stability of the model throughout the study period. Furthermore, the large and negative value of the error correction term (-0.7005) confirms the robust self-correcting mechanism of the system. Nepal has a very strong agricultural system, with large year-on-year adjustments to departures from equilibrium of over 70%.

These results have implications for policy. They begin by emphasizing the necessity of designing for resilience, particularly the well management of irrigation. Developing the concept of climate-smart agriculture and investing on it, such as drainage improvement, drought and disease resistant crop varieties, and early warning systems in regard to weather forecasting, might help reduce the harm caused by pre-monsoon and high temperatures. On the other hand, the benefits of post-monsoon rainfall suggest that some practices, such as conservation agriculture and mulching, which enhance soils' ability to hold moisture, may help to increase production in the context of shifting rainfall patterns.

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Finally, the significant upward temporal trend suggests that non-climatic factors like market integration, improved governance, and technology adoption would have also contributed to the observed increase in production. Therefore, governments need to balance agricultural development goals with climate adaptation to sustain and increase agriculture production.

Conclusion

This study examined the long-term and dynamic effects of climate-related factors like seasonal rainfall (pre-monsoon, monsoon and post-monsoon) and temperature (Tmax and Tmin) on paddy production in the hilly region of Nepal from 1990 to 2023 using Autoregressive Distributed Lag (ARDL) modelling. The study focused on how seasonal rainfall patterns and temperature fluctuations impact paddy production in hilly, climate-sensitive regions by integrating long-term agricultural and meteorological data.

The findings demonstrate that post-monsoon rainfall considerably and favorably promotes paddy yield, especially during the grain-filling and ripening stages. On the other side, pre-monsoon rainfall has a negative long-term effect, probably due to disruptions during the early stages of planting and field preparation. Unexpectedly, monsoon rainfall and temperature extremes (Tmax and Tmin) were not found to be significant over the long term. Therefore, it is suggesting that the pre-monsoon and post-monsoon distribution of climatic variables has a greater impact on paddy yield than monsoon rainfall.

Additionally, short-run dynamics demonstrate that heat stress from high temperatures and excessive rainfall during harvesting seasons have a significant detrimental effect on paddy production. These results were found that how vulnerable agricultural systems are to brief climate shocks, underscoring the necessity of targeted adaptive strategies such as improved irrigation systems, managed drainage, the use of drought-tolerant seed varieties, and the shifting of planting and harvesting times. The results have credibility because of the ARDL model's robustness, which has been confirmed by numerous diagnostic checks and stability tests. A robust self-correcting mechanism in the agricultural system is confirmed by the considerable error correction term, indicating that the region's agriculture is somewhat resilient to climate variability and gradually adjusts towards equilibrium.

All things considered, this study provides empirical data that can guide Nepal's agriculture policy for climate resilience. Policymakers should consider not just the annual totals but also the distribution and time of rainfall when making decisions. Additionally, they ought to invest in climate-smart infrastructure, climate-smart agriculture, and early warning systems regarding weather forecasting. As climate change continues to disrupt hydrological and thermal regimes, localized assessments which are essential to ensure food security and sustainable agricultural growth in sensitive places like mid-hill agro-ecological region of Nepal.

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