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Research Paper

Climate change and its effects on maize yield in Nepal: An empirical analysis using the ARDL model

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ABSTRACT

This study analyzes the impact of climate change on maize yield in Nepal's Gulmi (hilly) and Rupandehi (Terai) districts using climatic data from 1981 to 2023 on rainfall, relative humidity, maximum temperature, and minimum temperature applying the Autoregressive Distributed Lag (ARDL) model. The findings obtained ARDL model shows that rainfall positively influences yield in both regions. Relative humidity has a positive long-term effect in Gulmi but a negative impact in Rupandehi. Maximum temperature increases yield in Gulmi but significantly reduces it in Rupandehi, indicating regional sensitivity. Minimum temperature negatively affects Gulmi yields but has a negligible positive effect in Rupandehi. The ARDL models demonstrate strong explanatory power, with adjusted R^2 values of 0.86 (Gulmi) and 0.80 (Rupandehi), confirming a significant long-term relationship between climate variables and yield. Error correction terms suggest that 28% (Gulmi) and 30% (Rupandehi) of short-term yield deviations adjust back to long-run equilibrium annually. These results highlight the importance of localized climate adaptation strategies in agriculture.

Keywords: Climate Change, Maize Yield, ARDL Model, Cointegration Approach, Unit Root Test, Nepal

Nepal is a landlocked country with a subtropical climate that experiences extreme weather conditions. Agriculture, heavily reliant on climate, is significantly impacted by these changes (Sharma, 2010). Bhatta *et al.,* (2024) studied the impact of GHG emissions, temperature, and precipitation on rice production in Nepal using time series data from 1990 to 2019 and reported that GHG emission had a significant positive impact and the annual average mean temperature had a significant negative impact on rice production in Nepal. Addressing the adverse effects of climate change on agriculture is essential, especially in the hilly regions where food insecurity is high. Area-specific and crop-specific research is crucial to mitigate these impacts (Bhatta *et al.,* 2024). The econometric models have been widely used across the globe to study the effects of climatic factors on crops like cassava output in Nigeria (Aberji *et al.,* 2025), rice production in Nepal and Korea (Bhatta *et al.,* 2024; Nasrullah *et al.,* 2021), sugarcane in Pakistan (Ali *et al.,* 2021) and maize production in Nepal (Chandio *et al.,* 2022) and tea production in India (Premkumar *et al.,* 2025).

Since maize is a major staple crop of Nepal, analyzing its response to climate change will help develop effective policies and strategies to minimize the adverse effects. Given increasing threats to food security in Nepal, it is imperative to conduct detailed, empirical studies that assess how different climatic variables interact with maize yield at a micro-level. This study aimed to fill this research gap by analysing past climate and yield data using the Auto Regressive Distributed Lag (ARDL) model proposed by Pesaran *et al.,* (2001), providing insights that can guide climate-resilient agricultural planning and policy formulation.

MATERIAL AND METHODS

Study area

The Gulmi district characterized by hilly landscapes and Rupandehi districts located in the Terai region of Nepal were considered for the present study. Gulmi district is situated at an altitude ranging from 600 m to 2,900 m above mean sea level (MSL)

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and lies at 28.05° N latitude and 83.25° E longitude. In contrast, Rupandehi district is positioned at a lower altitude of 100 m to 300 m above MSL, with coordinates of 27.5° N latitude and 83.4° E longitude. The agro-ecological zones of these districts are distinctly different. Terai districts like Rupandehi are more susceptible to floods, heat waves, and irregular monsoon patterns, whereas hilly districts like Gulmi contend with landslides, droughts, and dwindling water sources. This contrast makes the study particularly relevant for analysing the impact of climate change on maize yield across different agro-climatic zones.

Data and methodology

The production and yield data of maize for the period of 1981–2023 were collected from Statistical Information on Nepalese Agriculture from the Ministry of Agriculture and Central Bureau of Statistics, Thapathali, Kathmandu, Nepal. The climatic data on minimum temperature, maximum temperature, relative humidity, and rainfall, were obtained from the Resunga (Tamghas) Meteorological Station for Gulmi district and from the Bhairahawa Airport Meteorological Station Rupandehi district, Department of Hydrology and Meteorology (DHM), Govt of Nepal.

Auto Regressive Distributed Lag model (ARDL) proposed by Pesaran *et al.,* (2001) has been chosen to analyze the effects of independent climatic factors on the yield of maize in the Gulmi and Rupandehi districts of Nepal. The basic model has been constructed as follows,

$$Yield = \alpha_0 + \alpha_1 Rain + \alpha_2 RHu + \alpha_3 Tmax + \alpha_4 Tmin + \epsilon_t \quad (1)$$

Where, Yield is the yield of maize in kg per ha, Rain is the annual rainfall in mm, RHu is the relative humidity in %, Tmax is the maximum temperature and Tmin is the minimum temperature in degrees Celsius.

The variables are converted into natural log format as follows,

$$lnYield = \alpha_0 + \alpha_1 lnRain + \alpha_2 lnRHu + \alpha_3 lnTmax + \alpha_4 lnTmin + \epsilon_t \quad (2)$$

α_0 represents the drift component in both equations, and α1 to α4 represent the respective coefficients.

Equation 2 can be represented in the ARDL form as,

$$lnYield = \alpha_0 + \sum_{i=0}^{p} \alpha_1 LnRain_{t-k} + \sum_{i=0}^{p} \alpha_2 \Delta LnRHu_{t-k} + \sum_{i=0}^{p} \alpha_3 \Delta LnTmax_{t-k}$$
$$\sum_{i=0}^{p} \alpha_4 \Delta LnTmin_{t-k} + \sum_{i=0}^{p} \beta_1 LnRain_{t-k} + \sum_{i=0}^{p} \beta_2 LnRHu_{t-k} +$$
$$\sum_{i=0}^{p} \beta_3 LnTmax_{t-k} + \sum_{i=0}^{p} \beta_4 LnTmin_{t-k} + \varepsilon_t$$
(3)

Where, is the first difference, is the drift, and ε_t is the white noise. The optimum lag length is selected for the study using the Akaike Information Criterion. The model initially identifies the long-run association between the variables. Subsequently, it applies the error correction model to determine the short-run relationship between the explanatory and explained variables. The error correction model includes the short-run coefficients and the error correction term for the long run.

The Augmented Dickey-Fuller test was used to assess the stationarity of the variables, confirming whether the data is stationary at level form, first difference, or a mixed order. Model (2) estimated the core coefficients, followed by the Wald-F test to check for cointegration. If the F statistic exceeded the upper limit, it confirmed cointegration among the variables, allowing the use of OLS methods for model estimation.

Table 1: Correlation between maize yield and weather parameters

Variables	Correlation coefficient	
	Gulmi	Rupandehi
Rainfall (Rain)	0.816*	0.822*
Relative humidity (RHu)	0.797*	0.741*
Maximum temperature (Tmax)	-0.692*	-0.681*
Minimum temperature (Tmin)	0.170	0.341*

(* significant at 5% level of significance)

RESULTS AND DISCUSSION

Trends in maize yield and correlation with climatic parameters

The maize yield showed an increasing pattern in both Gulmi and Rupandehi districts, (Fig. 1). Table 1 shows the correlation of the weather parameters with the maize yield. Rainfall (Rain) and relative humidity (RHu) show a strong, positive, and significant correlation with the dependent variable in both districts. Maximum temperature (Tmax) has a significant but negative correlation in both regions (Gulmi: -0.692, Rupandehi: -0.681), which means it negatively affects the yield, alternatively, cooler temperatures are more favourable for a better yield. Minimum temperature (Tmin) shows a weak and non-significant correlation in Gulmi (0.170), but moderately and positively significant (0.341) in Rupandehi. Further, the study of the correlation coefficients reveals the interdependency between the variables under consideration.

Unit root test

The primary requirement for the ARDL model is that the variables should be stationary at level form, I (0), or at the first difference, I (1). The unit root test used in the study is the Augmented Dicky Fuller Test. The results show that the variables are stationary at a mixed order of 0 and 1; this allows us to apply the ARDL model to analyze climate effects on maize crop yield, our dependent variable (Table 2).

Lag selection

We used the Akaike Information Criteria (AIC) to select the optimal lag. The maximum lag length is three, and then the AIC values associated with each potential model are tested for both regions. Out of the 16 candidate models evaluated for Gulmi and 15 for Rupandehi, ARDL (2,3,0,0,2) and ARDL (2,3,0,2,0) models, respectively, were chosen as the best models, based on the lowest AIC values. The ARDL Bound Test was conducted to identify cointegration between the variables under study. The test results indicate that the F-statistic values (5.75 for Gulmi maize and 5.94 for Rupandehi maize) exceed their corresponding upper bound (4.92 and 5.06), leading to the rejection of the null hypothesis at the 1% significance level. Therefore, it is concluded that the variables

Table 2: Unit root test results for checking the stationarity of the variables

Variable	Gulmi		Rupandehi		First difference	Gulmi		Rupandehi	
	Test	P value	Test	P value		Test	P value	Test	P value
LnYield	-3.35	0.07	-2.06	0.54	ΔLnYield	-5.13	0.01	-6.65	0.01
LnRain	-2.14	0.51	-2.29	0.45	ΔLnRain	-3.97	0.02	-3.98	0.01
LnRHu	-3.05	0.15	-3.11	0.13	ΔLnRHu	-4.26	0.01	-4.40	0.01
LnTmax	-2.87	0.22	-2.75	0.27	ΔLnTmax	-4.48	0.01	-4.59	0.01

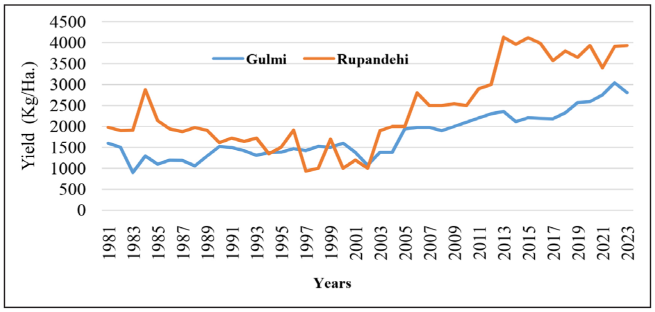

Fig. 1: Maize yield in Gulmi and Rupandehi districts

under study are cointegrated, indicating a long-term association between the climatic variables and maize yield in both study areas. Subsequently, the ARDL model was employed to identify the coefficients.

The resulting analysis demonstrates the long-run relationship between the dependent and independent variables (Table 3). The model exhibits a remarkably high R^2 value of 0.90 for Gulmi and 0.86 for Rupandehi, along with adjusted R^2 values of 0.86 and 0.80, respectively. This suggests that the model effectively explains 86% and 80% of the long-run variation in maize yield for Gulmi and Rupandehi districts, as indicated by the adjusted R^2 values. The cointegrating equations show the short-run effects of the climatic variables on the yield of the maize crop and the long-run correction, or the ECM term, for the long-run correction of the short-run coefficients of the model for both Gulmi and Rupandehi maize yields (Table 3).

Short-run and long-run effects of climate change on the yield of maize

The short-run and long-run coefficients of climatic factors under study reveal the following results in both regions. A year's yield positively affects the yield of consecutive years in the long run, whereas its effect is adverse in the short run. A high yield in the current year might help the farmers find more leisure in the next year, resulting in reduced yield in the subsequent year. On the other hand, a low yield might force them to put more time and resources next year, hence improve the yield. This behaviour can potentially cause a negative relationship between the yields of consecutive years in the short run. However, farmers can learn this in the long run and behave more rationally. They will invest more in technologies, better seeds, etc., leading to even higher yields. The current result shows a similar trend where an apparent price effect can be implicitly observed in the intertemporal relationship between annual yields.

The effects of climatic variables (rainfall, relative humidity, maximum temperature, and minimum temperature) are also analysed, looking at their short-term and long-term effects on maize yield separately. In both the study regions, the rainfall effect is minutely positive and statistically significant, but the effect of their consecutive lag years is not significant. Chandio *et al.,* (2022) also reported a positive yet insignificant impact of rainfall on maize production in Nepal. The long-term effect of relative humidity is minutely positive but non-significant and is not included in the short-run model for both regions. While relative humidity does not affect in the short run, its effect is positive in the long run. Czarnecka *et al.,* (2022) observed that hefty rainfall and high air humidity greatly influenced the incidence of diseases in maize. However, in the long run, it is seen that the effect of relative humidity is positive. An 1% increase in the first lag value of relative humidity seems to increase the maize yield by 0.12% for Gulmi and decrease the maize yield by 1.08% for Rupandehi.

The study focuses on a temperate region, where rising temperatures initially boost maize crop yields by enhancing metabolism and photosynthesis. Specifically, 1% increase in maximum temperature raises yields by 0.97% in Gulmi but decreases them by 2.32% in Rupandehi. In the short run, maximum temperature does not impact yields in Gulmi, but it does affect in Rupandehi district. Rising temperatures have notably altered the cropping patterns for rice producers in Nepal (Bhatta *et al.,* 2024).

Minimum temperature impacts are negative in Gulmi district in the short and long run, with 1% increase in its one-year lag value reducing yields by 0.53% long term and 1.15% short term. However, in the long run, 1% increase in the two-year lag of minimum temperature raises yields by 1.15%. In Rupandehi district, the effect of minimum temperature is slightly positive in the long run but negligible in the short term, increasing yield by 0.04%. The error correction terms indicate that annually, 28% of short-run disequilibrium in Gulmi and 30% in Rupandehi adjust to long-run equilibrium.

Diagnostic checks

The test results indicate a good model fit, with an R^2 value of 0.90 and an adjusted R^2 of 0.86 for the Gulmi district, meaning the independent variables explain 86% of maize yield variation (Table 3). Similarly, for Rupandehi, the model shows an adjusted R^2 of 0.80, indicating that climatic variables explain 80% of the variation in maize yield. The Breusch-Godfrey LM test (1.47 for Gulmi and 0.72 for Rupandehi) indicates no statistically significant serial correlation in either model. The Breusch-Pagan test (1.59 and 1.40) confirms no significant heteroscedasticity, suggesting the

Table 3: ARDL and Cointegrating models for long-run and short-run effect of climatic parameters on maize yield in Gulmi and Rupandehi districts of Nepal

Districts	Long run models	R^2	Adj R^2
Gulmi ARDL (2, 3, 0, 0, 2)	LnYield = 0.44LnYield (-1) +0.26LnYield (-2) + 0.15LnRain + 0.02LnRain(-1) + 0.03ln-Rain(-2) – 0.005lnRain(-3) + 0.12LnRHu + 0.97LnTmax -0.53LnTmin+0.31LnTmin (-1) +1.15LnTmin (-2) - 4.81	0.90	0.86
Rupandehi ARDL (2, 3, 0, 2, 0)	LnYield = 0.43 LnYield(-1) + 0.03 LnYield(-2) + 0.32 LnRain + 0.11 LnRain(-1) - 0.37 Lnrain(-2) + 0.34 LnRain(-3) – 1.08 LnRHu - 2.32 LnTmax + 0.68 LnTmax(-1) – 4.18 LnT-max(-2) + 0.04 LnTmin + 26.55	0.86	0.80
	Cointegrating Equations		
Gulmi	D(LnYield) = -0.26 LnYield (-1) + 0.15 LnRain – 0.03 LnRain(-1) + 0.005 LnRain(-2) – 0.53LnTmin - 1.15 LnTmin(-1) - 0.28	0.50	0.48
Rupandehi	D(LnYield) = -0.03 LnYield(-1) + 0.32 LnRain + 0.03 LnRain(-1) – 0.34 LnRain(-2) - 2.32 LnTmax + 4.18 LnTmax(-1) – 0.30	0.59	0.49

model residuals are homoscedastic and free from serial correlation for maize yield in both regions. Additionally, the Jarque-Bera test, where the test statistics are 0.422 for Gulmi and 0.530 for Rupandehi, shows that the residuals are normally distributed. ACF and PACF plots of residuals also reveal no significant autocorrelation in either model.

CONCLUSIONS

The study revealed that in Gulmi and Rupandehi districts rainfall significantly influences maize yields. Relative humidity can have ambiguous effects; while increased humidity may trigger diseases in the short term, its overall impact remains unclear. The study indicates that maximum temperature generally has a positive long-term effect, provided it does not exceed optimal levels. Despite these insights, the research has limitations, such as its focus on only two districts, which may not apply to other regions or crops. Data constraints and simplifications in modeling may overlook the complexities of maize production, including external factors like market dynamics and policy interventions. Future projections should be approached cautiously due to uncertainties in climate change and socio-economic conditions. Overall, the research emphasizes the need for further studies and targeted policies to enhance maize production in Nepal.

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REFERENCES

Ali, S., Zubair, M. and Hussain, S. (2021). The combined effect of climatic factors and technical advancement on yield of sugarcane by using ARDL approach: Evidence from Pakistan. *Environ. Sci. Pollut. Res.,* 28: 39787-39804.

Aberji, O. D., Oyita, G. E. and Enwa, S. (2025.) Combined effect of rainfall and sunshine duration on cassava output in Nigeria. *J. Agrometeorol.,* 27(2): 163-167. https://doi.org/10.54386/jam.v27i2.2935

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

Chandio, A. A., Akram, W., Bashir, U., Ahmad, F., Adeel, S. and Jiang, Y. (2022). Sustainable maize production and climatic change in Nepal: Robust role of climatic and non-climatic factors in the long-run and short-run. *Environ. Dev. Sustain.,* 25(2): 1614-1644.

Czarnecka, D., Czubacka, A., Agacka-Mołdoch, M., Trojak-Goluch, A. and Księżak, J. (2022). The Occurrence of Fungal Diseases in Maize in Organic Farming Versus an Integrated Management System. *Agron.,* 12(3): 558.

Nasrullah, M., Rizwanullah, M., Yu, X., Jo, H., Sohail, M. T. and Liang, L. (2021). Autoregressive distributed lag (ARDL) approach to study the impact of climate change and other factors on rice production in South Korea. *J. Water Clim. Change.,* 12(6): 2256-2270

Pesaran, M. H., Shin, Y. and Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *J. App. Econ.,* 16 (3): 289-326.

Premkumar, A., Kishan, R., and D. Kalaiarasi. (2025). Repercussions of climatic variabilities on tea production in Nilgiris district of Tamil Nadu, India. *J. Agrometeorol.,* 27(2):173-176. https://doi.org/10.54386/jam.v27i2.2902

Sharma, S. (2010). Climate change impact on livelihood and vulnerability: A case study of mushar community in saptari district in Nepal (Doctoral dissertation, BRAC University).