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Short-Term and Long-Term Effects of Climatic and Non-Climatic Factors on Maize Yield over a 33 Year Period (1990–2022) in Nepal

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ABSTRACT: The objective of this paper was to investigate the short-term and long-term effects of climatic and non-climatic factors on maize yield over a 33 year period (1990–2022) in Nepal using an Autoregressive Distributed Lag (ARDL) model. The study examines the role of temperature, rainfall, pesticide use, and carbon dioxide (CO_2) emissions (per capita and agricultural) in shaping maize productivity. The results show that temperature has an insignificant long-run influence on maize yield. Rainfall shows a significant negative effect in the short-term (-0.861224, p = 0.0424) but a positive but insignificant long-run effect (1.963022, p = 0.1792). Pesticide use significantly increases maize yield, both in the short run (2.093082, p = 0.0095) and the long run (14.35734, p = 0.0000). CO_2 emissions per capita (CO_2PC) positively affect maize yield in the long run (18754.80, p = 0.0012), whereas agricultural CO_2 emissions (CO_2AG) exhibit a significant negative impact on maize yield (-22074.70, p = 0.0001). Granger causality tests indicate that rainfall, temperature, and CO_2 emissions Granger-cause maize yield, with the feedback effect from agricultural emissions and productivity. These findings emphasize the need for sustainable farming practices to manage both climate change and agricultural input use effectively.

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Climate change has emerged as a significant factor influencing agricultural productivity globally, with variable impacts on crop yields, especially in developing countries where agriculture remains a key sector of the economy. In Nepal, the agricultural sector, including maize production, is highly sensitive to climatic variables such as temperature, rainfall, and the use of agricultural inputs (Bhandari, 2013; Aryal *et al.*, 2016). The effects of these climatic factors on crop productivity have been studied across different regions, but the dynamics remain complex due to interactions with non-climatic factors such as agricultural technology, pest management, and fertilizer use (Chandio *et al.*, 2022; Baig *et al.*, 2023).

In recent years, there has been increasing concern over the combined effects of climate change and agricultural practices on crop yield, particularly maize, which is a main food in many parts of Nepal (Khatri and Timsina, 2023). Temperature fluctuations and unpredictable rainfall patterns are among the primary climatic factors affecting maize productivity (Maharjan *et al.*, 2013; Khanal, 2015). As global temperatures continue to rise, these changes in

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weather patterns could exacerbate challenges in maize production, impacting food security (Ghosh *et al.*, 2023). Furthermore, while temperature and rainfall are important, non-climatic factors such as the use of pesticides and fertilizers also play a role in determining agricultural output (Li and Tian, 2024).

The role of Foreign Direct Investment (FDI) and technological advancements has been explored in several studies, with evidence suggesting that FDI and technology can either mitigate or exacerbate the negative impacts of climate change on crop yield (Ahmad *et al.*, 2020; Baig *et al.*, 2023). Technological advancements in irrigation, pest control, and fertilizer use have shown promise in enhancing resilience to climate stress and improving yields in countries such as Pakistan and India (Ali *et al.*, 2021; Baig *et al.*, 2023). However, the long-term sustainability of such practices remains a point of concern due to environmental impacts, particularly carbon dioxide (CO_2) emissions from agricultural activities (Chandio *et al.*, 2023).

The economic consequences of reduced maize yields due to climatic changes are particularly severe for smallholder farmers, as they directly affect household income and food availability (Egbetokun *et al.*, 2014; Guntukula and Goyari, 2020). Studies on the climatic risks associated with maize production highlight the need for adaptive strategies to mitigate potential losses (Harrison *et al.*, 2011; Chandio *et al.*, 2023). Furthermore, rising CO_2 emissions from agricultural practices and the increasing frequency of extreme weather events necessitate a focus on sustainable agricultural practices that can help stabilize maize production (Poudel *et al.*, 2014; Gul *et al.*, 2022).

Maize, a staple crop, plays a critical role in food security and economic stability, particularly in developing countries like Nepal, where agriculture is heavily dependent on climate and non-climate factors. Despite its significance, maize productivity faces substantial challenges due to climatic variability, including temperature fluctuations and erratic rainfall patterns, which threaten the stability of crop yields (Sounders *et al.*, 2017; Osman *et al.*, 2021). Moreover, the increasing use of pesticides, fertilizers, and the rise in CO_2 emissions from agricultural activities further complicate the situation, potentially exacerbating environmental degradation and long-term sustainability (Khan *et al.*, 2019). Climate change, with its unpredictable weather patterns, is expected to exacerbate these challenges, making it crucial to assess its impact on maize yields and devise adaptive strategies (Egbetokun *et al.*, 2014; Gul *et al.*, 2022). While several studies have explored the effect of climate change on crop yields globally, there is a lack of comprehensive research focusing on the combined effects of climatic and non-climatic factors on maize production in Nepal, particularly in relation to local conditions and farming practices (Guntukula and Goyari, 2020; Li and Tian, 2024). Understanding the complex interactions between these factors is essential for developing effective policies to ensure sustainable maize production in the face of ongoing climate challenges.

This study aims to analyze the combined effects of climatic and non-climatic factors, such as temperature, rainfall, pesticide use, and CO_2 emissions, on maize yield in Nepal. Using a time-series approach and Autoregressive Distributed Lag (ARDL) modeling, this research explores both the short-term and long-term impacts of these variables on maize productivity. The ARDL model is particularly useful for analyzing time-series data with variables integrated at different orders, allowing for a comprehensive analysis of both immediate and delayed effects (Noorunnahar *et al.*, 2023; Singh *et al.*, 2024).

In line with previous studies on the effects of climate change on agriculture in developing countries, this research will contribute valuable insights into how environmental and agricultural practices interact to shape maize yield in Nepal. Understanding these dynamics is crucial for developing effective policies that promote climate-resilient agriculture and ensure food security in the face of climate change (Chandio *et al.*, 2022). The findings will also inform recommendations on the role of sustainable farming techniques and the mitigation of environmental impacts through adaptive agricultural practices (Baig *et al.*, 2023; Chandio *et al.*, 2023). Given the increasing vulnerability of Nepal's agricultural sector to climate variability, it is crucial to bridge this gap by exploring how both environmental and agricultural inputs interact to affect maize yield in this region, especially in light of ongoing climate change. Consequently, the objective of this paper is to investigate the short-term and long-term effects of climatic and non-climatic factors on maize yield over a 33 year period (1990–2022) in Nepal.

MATERIALS AND METHODS

Study design: This study employs a quantitative research design to explore the short-term and long-term effects of climatic and non-climatic factors on maize yield in Nepal. The analysis utilizes a time-series econometric approach, specifically the ARDL model, which is well-suited for examining both short-run and long-run relationships among variables. The ARDL method allows for the inclusion of variables that are integrated at different orders (I(0) and I(1)) without requiring all variables to be of the same order, making it an appropriate choice for this study.

Data sources and study variables: The dataset consists of annual time-series data spanning from 1990 to 2022. The data were collected and compiled from reliable secondary sources including from Food and Agriculture Organization of the United Nations and Climate Change Knowledge Portal.

In this study, the dependent variable is *maize yield*, which is quantified in hectograms per hectare (hg/ha). The independent variables influencing maize yield include *average annual temperature* (measured in degrees Celsius °C), *total average rainfall* (measured in mm), *total quantity of pesticides used* (measured in tons), and *carbon dioxide (CO_2) emissions from agriculture* (measured in metric tons of CO_2 equivalent, Mt CO_2e). The analysis aims to assess how variations in these climatic and agricultural factors affect maize productivity.

Each variable was chosen based on its theoretical and empirical relevance to maize production, as established in previous literature. The variables, their symbols, units, and data sources are summarized in Table 1.

Table 1: Variables, Abbreviations, Units Used in Research

Variable names	Symbols	Units	Source
Yield of the Maize	Maize Yield	hectograms per hectare	FAO
CO_2 emissions Per Capita	CO_2PC	Metric tons per capita	WDI
Carbon dioxide emissions from Agriculture	CO_2AG	Metric tons CO_2e	WDI
Average annual temperature	Temperature	in Degrees Celsius	CCKP
Total average rainfall received	Rainfall	Average rainfall(mm/year)	CCKP
total quantity of pesticides used	Pesticides	Metric tons /year	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 (Maize Yield) at time t, X_{t-j} = represents the independent variables (temperature, rainfall, pesticides, CO_2PC and CO_2AG), 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.

The following steps have been used in ARDL analysis.

Stationarity test: To determine the order of integration of the variables, stationarity tests were performed using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. These tests ensure that the variables are either I(0) or I(1), as ARDL cannot handle I(2) variables.

Lag Length selection: The optimal lag length for the ARDL model was determined using criteria such as the Akaike Information Criterion (AIC) and Schwarz Bayesian Criterion (SBC). This ensures the inclusion of appropriate lag structures for both long-run and short-run analysis.

Bounds testing for cointegration: The ARDL bounds test was applied to check for the existence of a long-run equilibrium relationship among the variables. The null hypothesis (H_0) of no cointegration was tested against the alternative hypothesis (H_1) of cointegration (Pesaran *et al.*, 2001; Poudel *et al.*, 2024).

Estimation of long-run coefficients: If cointegration was confirmed, the long-run coefficients were estimated to determine the long-term impacts of the independent variables on maize yield.

Error correction model (ECM): The ECM was employed to capture short-term dynamics and the speed of adjustment towards long-run equilibrium. The error correction term (CointEqt−1) represents the rate at which short-term deviations are corrected (Pesaran and Shin, 1995).

Hypothesis testing: This research tests the following hypotheses:

i) H_1: Climatic factors such as temperature and rainfall significantly influence maize yield in the short and long term, and these factors cause changes in maize yield.

ii) H_2: Agricultural practices, including pesticide use, significantly impact maize yield in the short and long term, and pesticide use Granger causes changes in maize yield.

iii) H_3: Environmental factors such as CO_2 emissions per capita (CO_2PC) and agricultural CO_2 emissions (CO_2AG) significantly impact maize yield in the short and long term, and these emissions Granger cause changes in maize yield.

The following diagnostic tests were conducted to validate the model.
Jarque-Bera test: To check for normality of residuals.

Breusch-Godfrey test: To test for serial correlation.

Breusch-Pagan-Godfrey test: To test for heteroscedasticity.
Ramsey RESET test: To check for model specification errors.

CUSUM and CUSUMSQ tests: To assess model stability over time.

Assumptions and limitations: This study has a few key assumptions and limitations. It is assumed that the data used in the analysis are accurately reported and free from measurement errors, ensuring the reliability of the results. The ARDL model assumes linear relationships among variables, which may not fully capture the complex nonlinear dynamics that could exist in the relationship between climatic, agricultural, and environmental factors and maize yield. Furthermore, the model does not explicitly account for external factors such as policy changes or market shocks, which could influence maize yield and introduce potential biases or unobserved effects in the analysis. These assumptions and limitations highlight the need for careful interpretation of the findings within the scope of the study's methodological framework.

RESULTS AND DISCUSSION

Trends in key variables for the analysis: The analysis of 33 years of data illustrates distinct trends in key variables such as maize yield, temperature, rainfall, pesticide usage, and CO_2 emissions. Maize yield has shown an overall upward trend, but the variability in climatic factors like temperature and rainfall underscores the influence of environmental changes on agricultural performance, as depicted in Figure 1.

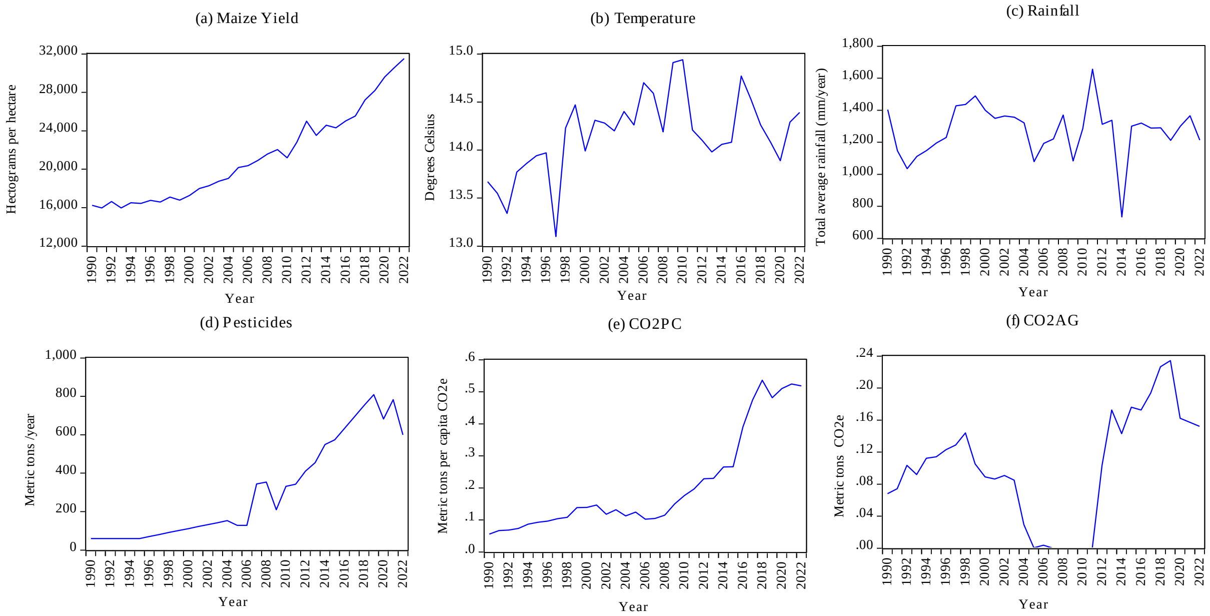

Fig. 1: Trends in Maize Yield, Temperature, Rainfall, Pesticides, and CO_2 Emissions

The trends depicted over the 33-year period (1990–2022) highlight the interplay between climatic variables and agricultural inputs in influencing maize yield in Nepal. Figure 1(a) shows a consistent upward trajectory in maize yield, reflecting improvements in agricultural practices and the use of inputs. However, temperature and rainfall trends, as shown in Figure 1(b) and Figure 1(c), exhibit significant variability, with irregular peaks and troughs underscoring the challenges of unpredictable climatic conditions. Rainfall patterns, in particular, appear erratic, highlighting the vulnerability of rain-fed agriculture to climate variability. Figure 1(d) shows a steady increase in pesticide usage, especially in recent years, indicating intensified pest management efforts to sustain and enhance yields, though this raises concerns about long-term environmental sustainability. Similarly, Figure 1(e) highlights a sharp rise in CO_2 emissions per capita (CO_2PC) mid-period, reflecting broader industrial and agricultural activities contributing to greenhouse gas emissions. Meanwhile, Figure 1(f) illustrates notable fluctuations in CO_2 emissions specifically from agriculture (CO_2AG), emphasizing the sector's dual role as both a contributor to and a victim of climate change. These trends collectively underscore the pressing need for adaptive and sustainable agricultural strategies to mitigate the adverse effects of climatic and environmental changes on maize production.

Descriptive statistics: Table 2 summarizes the descriptive statistics of key variables over 33 years, including maize yield, temperature, rainfall, pesticide usage, and CO_2 emissions. The data highlights variability in these factors, with maize yield averaging 21,233.79 hg/ha, while climatic and input variables show diverse ranges influencing agricultural productivity.

Table 2: Descriptive Statistics of Key Variables

	Maize Yield	Temperature	Rainfall	Pesticides	CO_2PC	CO_2AG
Mean	21233.79	14.16	1271.93	307.31	0.21	0.10
Median	20382.00	14.20	1300.03	153.00	0.14	0.10
Maximum	31519.00	14.94	1656.02	809.09	0.54	0.23
Minimum	15976.00	13.10	732.86	60.11	0.06	0.00
Std. Dev.	4666.45	0.41	161.20	256.90	0.16	0.07
Skewness	0.66	-0.35	-0.83	0.66	1.12	-0.06
Kurtosis	2.32	3.39	5.62	1.93	2.71	2.17
Observations	33	33	33	33	33	33

Table 3: Correlation Analysis

	Maize Yield	Temperature	Rainfall	Pesticides	CO_2PC	CO_2AG
Maize Yield	1					
Temperature	0.35	1				
Rainfall	-0.03	0.07	1			
Pesticides	0.94	0.30	-0.02	1		
CO_2PC	0.92	0.25	0.03	0.93	1	
CO_2AG	0.44	-0.26	-0.03	0.58	0.67	1

Table 4: Unit Root Test Results

Unit Root Test Table (PP)							
At Level		Maize Yield	Temperature	Rainfall	Pesticides	CO_2PC	CO_2AG
With Const.	t-Stat.	4.42	-3.07**	-4.61***	-0.52	0.54	-1.42
With Const.& T.	t-Stat.	-1.10	-3.58**	-4.56***	-2.34	-1.21	-1.56
None	t-Stat.	3.98	0.67	-0.56	0.82	2.24	-0.44
At First Difference		d(Maize Yield)	d(Temperature)	d(Rainfall)	d(Pesticides)	d(CO_2PC)	d(CO2AG)
With Const.	t-Stat.	-6.59***	-10.26***	-19.97***	-6.69***	-4.43***	-4.41***
With Const. & T.	t-Stat.	-8.97***	-15.50***	-19.44***	-6.56***	-4.56***	-4.35***
None	t-Stat.	-4.98***	-9.73***	-20.36***	-6.19***	-3.94***	-4.46***
Unit Root Test Table (ADF)							
At Level		Maize Yield	Temperature	Rainfall	Pesticides	CO_2PC	CO_2AG
With Const.	t-Stat.	2.63	-3.22**	-4.61***	-0.67	0.78	-4.41***
With Const.& T.	t-Stat.	-1.39	-3.64**	-4.56***	-2.46	-2.40	-4.52***
None	t-Stat.	3.98	0.23	-0.24	0.55	2.51	-0.30
At First Difference		d(Maize Yield)	d(Temperature)	d(Rainfall)	d(Pesticides)	d(CO2PC)	d(CO2AG)
With Const.	t-Stat	-6.66***	-6.56***	-8.16***	-6.68***	-4.42***	-4.41***
With Const. & T.	t-Stat.	-8.06***	-6.66***	-8.00***	-6.55***	-4.65***	-4.34***
None	t-Stat.	-4.63***	-6.59***	-8.30***	-6.17***	-3.88***	-4.46***

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

Table 2 shows the statistical characteristics of the key variables influencing maize production in Nepal over 33 years. The mean maize yield is 21,233.79 hg/ha, with a standard deviation of 4,666.45, reflecting moderate variability. Climatic variables like temperature and rainfall show relatively narrow ranges, with mean values of 14.16°C and 1,271.93 mm, respectively, suggesting consistent conditions over the period. However, rainfall displays a higher kurtosis (5.62), indicating the presence of extreme values. Non-climatic variables such as pesticide use and CO_2 emissions vary significantly, with pesticides showing a mean of 307.31 metric tons but a high standard deviation of 256.90, reflecting uneven application levels. CO_2PC (per capita emissions) and CO_2AG (agriculture-specific emissions) are positively skewed, with their distributions leaning towards higher values. These descriptive insights highlight the variability and extremes in both climatic and agricultural practices, emphasizing the complexity of their impact on maize yield.

The correlation analysis highlights the relationships between maize yield and key variables. Maize yield has a high positive correlation with pesticide usage (0.94) and CO_2PC (0.92), indicating that increased pesticide application and per capita CO_2 emissions are closely associated with higher yields. Temperature also shows a moderate positive correlation with maize yield (0.35), suggesting that small temperature variations may have supported crop growth. In contrast, rainfall displays a negligible negative correlation (-0.03) with maize yield, reflecting its limited or inconsistent influence on yield during the study period. CO_2AG (agriculture-specific emissions) has a moderate positive correlation with maize yield (0.44) but is negatively correlated with temperature (-0.26), underscoring the complexity of interactions between emissions, climate, and agricultural practices. These findings emphasize the significant role of non-climatic factors like pesticides and CO_2PC in influencing maize production.

Unit Root Testing

Table 4 presents results of the unit root test for used variables, analyzed using both the PP and ADF tests, at level and first difference. At the level, most variables, such as rainfall and temperature, become stationary with significance at 5% or 1% under certain specifications (e.g., with constant and trend). However, variables like Maize Yield and Pesticides fail to achieve stationarity at level, indicating non-stationary behavior.

At first difference, all variables, including d(Maize yield), d(Temperature), and d(CO_2AG), exhibit stationarity with high significance (1% level) under all specifications (with constant, constant and trend, or none). This confirms that these variables are integrated of order I(1), making them suitable for the ARDL model. These results underline the necessity of differencing to achieve stationarity for most variables and the robustness of the testing framework in capturing time-series properties critical for econometric 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 2. This ensures the inclusion of appropriate lag structures for robust long-run and short-run analysis (Poudel *et al*., 2024).

Table 5: Criteria of Lag Length Selection

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-591.1882	NA	2.18e+09	38.52827	38.80582	38.61875
1	-464.5106	196.1460	6572199.	32.67810	34.62093*	33.31142
2	-408.7096	64.80115*	2431474.*	31.40062*	35.00872	32.57677*

* indicates lag order selected by the criterion

Table 5 depicts the lag length selection results based on various criteria, including the AIC, SC, and Hannan-Quinn Criterion (HQ). The AIC identifies an optimal lag of 2, indicated by the lowest value (31.40062). The SC suggests a lag of 1, and the HQ also favors a lag of 2. The chosen lag length ensures the inclusion of sufficient past observations, enabling the ARDL model to capture both short-term dynamics and long-term relationships accurately. This selection is critical for maintaining model robustness and minimizing information loss during analysis.

ARDL model (baseline model): Table 6 provides the results of the baseline ARDL model, capturing the relationships between maize yield and its predictors. The model includes key variables such as temperature, rainfall, pesticide use, CO_2PC, and CO_2AG, with significant coefficients highlighting both immediate and lagged effects on maize yield.The ARDL (2, 0, 1, 1, 2, 2) model demonstrates the magnitude, direction, and speed of relationships between maize yield and key variables such as temperature, rainfall, pesticide use, CO_2PC, and CO_2AG.

Table 6: ARDL Baseline Model Results
ARDL(2, 0, 1, 1, 2, 2)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
Maize Yield(-1)	0.245419	0.116444	2.107621	0.0502
Maize Yield(-2)	0.326297	0.113863	2.865694	0.0107
Temperature	-115.0363	216.4658	-0.531430	0.6020
Rainfall	-0.861224	0.392551	-2.193919	0.0424
Rainfall(-1)	1.701956	0.421334	4.039446	0.0009
Pesticides	2.093082	0.967867	2.162572	0.0451
Pesticides(-1)	4.055942	1.255320	3.231001	0.0049
CO_2PC	148.9451	2750.447	0.054153	0.9574
CO_2PC(-1)	-4392.222	3207.732	-1.369261	0.1887
CO_2PC(-2)	12275.66	2782.127	4.412330	0.0004
CO_2AG	5934.322	2821.833	2.103002	0.0507
CO_2AG(-1)	-21123.00	3347.872	-6.309381	0.0000
CO_2AG(-2)	5734.426	2433.856	2.356107	0.0307
C	7814.175	3130.506	2.496138	0.0231

The lagged values of maize yield, Maize Yield (-1) and Maize Yield(-2), have significant positive coefficients of 0.245419 and 0.326297, respectively, indicating that past yields strongly influence current yields. These values suggest that the impact of previous yields diminishes over time but remains important for forecasting future productivity. The moderate size of the coefficients reflects a gradual carryover effect, showcasing persistence in yield patterns.

Temperature, with a coefficient of -115.0363, shows an insignificant negative effect (p = 0.6020), implying limited direct influence on maize yield in this study. Conversely, rainfall exhibits mixed effects: the immediate impact is negative (-0.861224, p = 0.0424), indicating that excess or insufficient rainfall may reduce yields in the short term. However, the one-period lagged rainfall [Rainfall (-1)] has a positive and significant coefficient of 1.701956 (p = 0.0009), highlighting its crucial role in boosting yields after sufficient time has passed for water to benefit crop growth. These findings underscore the varying speed of rainfall's influence on agricultural productivity.

Pesticides significantly impact maize yield both contemporaneously and with a lag. The immediate effect (coefficient: 2.093082, p = 0.0451) and one-period lagged effect (coefficient: 4.055942, p = 0.0049) are both positive, with the lagged impact being nearly twice as large. This suggests that while pesticides improve yields quickly, their benefits accumulate over time, reflecting both short-term efficacy and longer-term enhancement of crop health. For CO_2PC (per capita emissions), the immediate coefficient (148.9451, p = 0.9574) is insignificant, but the two-period lag is highly significant and positive (12275.66, p = 0.0004). This substantial magnitude indicates that the effects of CO_2PC are delayed, with emissions influencing maize yield positively after a considerable lag. Similarly, CO_2AG (agricultural emissions) exhibits a dynamic pattern: an immediate positive impact (5934.322, p = 0.0507), a strongly negative one-period lag (-21123.00, p = 0.0000), and a positive two-period lag (5734.426, p = 0.0307). These results suggest both short-term benefits and potential medium-term detriments, followed by recovery, reflecting complex environmental and productivity dynamics. This ARDL analysis provides a detailed understanding of how climatic and non-climatic factors influence maize yield, considering both the speed and magnitude of their effects, enabling informed decisions for sustainable agricultural planning.

ARDL Long Run Form and Bounds test: Table 7 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 7: ARDL Bounds Test Results

Test Stat.	Value	Level of Significant	I(0)	I(1)
		Asymptotic: n=1000		
F-statistic	20.52321			
K	5	5%	2.39	3.38
Actual Sample Size	31	Finite Sample: n=35		
		5%	2.804	4.013
		Finite Sample: n=30		
		5%	2.91	4.193

Table 7 outlines the results of the ARDL bounds test, used to determine the existence of a long-run equilibrium relationship among the variables. The null hypothesis of "no levels relationship" is tested against the alternative hypothesis of a long-run relationship. The calculated F-statistic is 20.52321, which is significantly higher than the upper bound critical values (I(1)) across all significance levels (1%, 2.5%, 5%, and 10%). For example, at the 5% level, the critical bounds are 2.39 (I(0)) and 3.38 (I(1)) for an asymptotic sample, while for a finite sample size of 31, the bounds are 2.804 (I(0)) and 4.013 (I(1)). This result confirms the rejection of the null hypothesis, validating the presence of a cointegration relationship among the variables. The long-run relationship implies that despite short-term fluctuations, the variables maintain a stable association over time. The robustness of the test, as demonstrated by consistent results across asymptotic and finite sample bounds, ensures reliability in confirming this relationship. This is critical for modeling and interpreting the sustainable impacts of climatic and non-climatic factors on maize yield in Nepal.

Table 8: Short Run Coefficients

Variable	Coeff.	Standard Error	t-Stat.	Probability
D(Maize Yield(-1))	-0.326297	0.071842	-4.541881	0.0003
D(Rainfall)	-0.861224	0.255088	-3.376192	0.0036
D(Pesticides)	2.093082	0.716620	2.920769	0.0095
D(CO_2PC)	148.9451	1651.812	0.090171	0.9292
D(CO_2PC(-1))	-12275.66	2042.341	-6.010584	0.0000
D(CO_2AG)	5934.322	1824.596	3.252403	0.0047
D(CO_2AG(-1))	-5734.426	1632.619	-3.512409	0.0027
CointEq(-1)*	-0.428284	0.030720	-13.94155	0.0000

The ARDL model output reveals the immediate impacts of key climatic and non-climatic variables on maize yield, measured in hectograms per hectare (hg/ha). A 1 mm increase in rainfall (D(Rainfall)) results in a 0.861224 hg/ha decrease in maize yield, with a significant p-value of 0.0036. This indicates that excess or poorly timed rainfall negatively affects crop productivity. Conversely, a 1 metric ton increase in pesticide use (D(Pesticides)) significantly increases maize yield by 2.093082 hg/ha (p = 0.0095), underscoring the importance of pest management for boosting short-term agricultural outcomes.

CO_2 emissions demonstrate complex effects. A 1 metric ton per capita increase in CO_2PC (per capita CO_2 emissions) has an immediate but insignificant effect on maize yield (coefficient: 148.9451, p = 0.9292). However, a 1 metric ton per capita increase in CO_2PC with a one-period lag (D(CO_2PC(-1))) reduces maize yield significantly by 12275.66 hg/ha (p = 0.0000). Similarly, for agricultural CO_2 emissions (CO_2AG), a 1 metric ton increase in D(CO_2AG) results in a significant immediate yield gain of 5934.322 hg/ha (p = 0.0047), while a 1 metric ton increase in D(CO_2AG(-1)) causes a reduction of 5734.426 hg/ha (p = 0.0027). These contrasting effects illustrate the nuanced and time-sensitive nature of emissions' influence on crop productivity.

The error correction term (CointEq(-1)) captures the adjustment speed to restore equilibrium after short-run deviations. Its coefficient of -0.428284 indicates that approximately 42.8% of the deviations from the long-run equilibrium are corrected each year, with a highly significant p-value (p = 0.0000). This rapid adjustment demonstrates the resilience of maize yield to short-term shocks. This analysis highlights the critical short-run dynamics of rainfall, pesticide use, and emissions on maize yield, providing actionable insights for improving agricultural practices in Nepal.
Long Run coefficients: Table 9 presents the long-run coefficients from the ARDL model, showing the sustained impacts of temperature, rainfall, pesticides, CO_2PC, and CO_2AG on maize yield. Pesticides and CO_2PC exhibit significant positive effects, while CO_2AG negatively influences yield over time.

Table 9: Long Run Coefficients of Key Variables

Equation (Levels)				
Variable	Coeff.	Standard Error	t-Stat	Probability
Temperature	-268.5981	520.1404	-0.516395	0.6122
Rainfall	1.963022	1.401290	1.400868	0.1792
Pesticides	14.35734	2.516789	5.704628	0.0000
CO_2PC	18754.80	4845.183	3.870814	0.0012
CO_2AG	-22074.70	4383.879	-5.035428	0.0001
C	18245.30	7263.013	2.512084	0.0224

*EC = Maize Yield - (-268.60*Temperature + 1.96*Rainfall +14.36*Pesticides + 18754.80*CO_2PC -22074.70*CO_2AG + 18245.30)*

The long-run coefficients from the ARDL model capture the sustained impacts of key variables on maize yield, measured in hectograms per hectare (hg/ha). The results indicate that a 1°C increase in temperature reduces maize yield by 268.5981 hg/ha, but this effect is statistically insignificant (p = 0.6122), suggesting minimal direct influence of long-term temperature changes on yield within the context of this model.

Rainfall has a positive long-term effect, with a 1 mm increase in rainfall leading to a 1.963022 hg/ha increase in maize yield, although this relationship is not statistically significant (p = 0.1792). Conversely, the effect of pesticides is highly significant (p = 0.0000), with a 1 metric ton increase in pesticide use associated with a substantial 14.35734 hg/ha increase in maize yield, highlighting the critical role of pest management in sustaining long-term agricultural productivity.

CO_2 emissions reveal contrasting long-term impacts. A 1 metric ton per capita increase in CO_2PC (per capita CO_2 emissions) results in a 18754.80 hg/ha increase in maize yield, with a significant p-value of 0.0012. This indicates a positive association between industrial development and yield, possibly reflecting technological advancements or resource availability. On the other hand, a 1 metric ton increase in agricultural CO_2 emissions (CO_2AG) reduces maize yield significantly by 22074.70 hg/ha (p = 0.0001), underscoring the adverse environmental consequences of agricultural practices contributing to greenhouse gas emissions.

The constant term (C) of 18245.30 hg/ha is also significant (p = 0.0224), representing the baseline maize yield when all other variables are held constant. The error correction equation (EC) further describes how deviations in maize yield from its equilibrium path are influenced by these factors, providing a comprehensive view of long-term agricultural dynamics.

These results highlight the nuanced roles of climatic and non-climatic variables in shaping long-term maize yield, emphasizing the need for balanced and sustainable agricultural practices to mitigate adverse environmental impacts while maximizing productivity.

The Wald test: Table 10 summarizes the results of the Wald Test, confirming the joint significance of the independent variables in the ARDL model. The high F-statistic (9.598072, p = 0.0001) and Chi-square value (57.58843, p = 0.0000) validate the combined influence of these variables on maize yield. The Wald Test evaluates the joint significance of selected independent variables in the ARDL model (Khatri *et al.*, 2024), testing the null hypothesis that these variables have no influence on maize yield (C(2) = C(3) = C(4) = C(5) = C(6) = C(7) = 0).

Table 10: Wald Test Results for Joint Significance of Variables

Test Stat.	Value	Degree of freedom	Prob.
F-stat.	9.598072	(6, 17)	0.0001
Chi-square	57.58843	6	0.0000
H_0: C(2)=C(3)=C(4)=C(5)=C(6)=C(7)=0			
Normalized Restriction (= 0)		Value	Standard. Error
C(2)= D(Rainfall)		0.326297	0.113863
C(3)= D(Pesticides)		-115.0363	216.4658
C(4)= D(CO_2PC)		-0.861224	0.392551
C(5)= D(CO_2PC(-1))		1.701956	0.421334
C(6)= D(CO_2AG)		2.093082	0.967867
C(7)= D(CO_2AG(-1))		4.055942	1.255320

The results strongly reject this hypothesis, with an F-statistic of 9.598072 (p = 0.0001) and a Chi-square value of 57.58843 (p = 0.0000), confirming that the variables collectively and significantly affect maize yield. The individual coefficients reveal nuanced contributions: D(Rainfall (C(2)) has a modest but significant positive effect (0.326297, standard error: 0.113863), while D(Pesticides (C(3)) shows a negative value (-115.0363) but with high variability.

CO_2PC and CO_2AG exhibit mixed impacts, with contemporaneous and lagged effects reflecting their complex roles in influencing yield. For example, D(CO_2AG (C(6)) and its lag (C(7)) contribute significantly with positive coefficients of 2.093082 and 4.055942, respectively. These findings highlight the critical importance of analyzing these variables jointly, as their interconnected impacts provide a more comprehensive understanding of factors affecting maize yield.

Granger Causality test: Table 11 summarizes the Granger causality results, indicating directional relationships between variables. Rainfall and CO_2PC are shown to Granger-cause maize yield, highlighting their predictive influence on agricultural productivity.

Table 11: Results of Granger Causality Test

H_0	Observations	F-Stat.	Probability
Temperature →Maize Yield	31	6.14098	0.0065
Rainfall →Maize Yield	31	5.28778	0.0118
Maize Yield →CO_2PC		4.38822	0.0228
Rainfall → CO_2PC		4.83765	0.0164
Pesticides →CO_2PC		6.89419	0.0040
CO_2PC →CO_2AG		5.31640	0.0116

The Granger causality test examines whether one variable can predict another by rejecting the null hypothesis of no causal relationship (Khatri *et. al.*, 2025). The results highlight key directional dependencies among the variables in the model. Temperature is shown to Granger-cause maize yield, with an F-statistic of 6.14098 (p = 0.0065). This indicates that changes in temperature significantly predict variations in maize yield, underscoring its critical role in agricultural productivity. Similarly, rainfall also Granger-causes maize yield, as evidenced by an F-statistic of 5.28778 (p = 0.0118). This finding reflects the importance of rainfall in shaping crop outcomes, particularly in rain-fed systems like those common in Nepal.

The test also reveals feedback effects. Maize yield Granger-causes per capita CO_2 emissions (CO_2PC), with an F-statistic of 4.38822 (p = 0.0228). This suggests that agricultural productivity can influence emissions, potentially through economic activities related to resource use. Rainfall Granger-causes CO_2PC as well, with an F-statistic of 4.83765 (p = 0.0164), indicating that climatic variability may affect emissions indirectly through energy or resource consumption patterns.

Pesticide use Granger-causes CO_2PC, with an F-statistic of 6.89419 (p = 0.0040). This highlights the link between agricultural inputs and emissions, as increased pesticide application often correlates with higher resource and energy demands. Furthermore, per capita CO_2 emissions (CO_2PC) Granger-cause agricultural CO_2 emissions (CO_2AG), with an F-statistic of 5.31640 (p = 0.0116), reflecting a strong predictive relationship between general and agriculture-specific emissions.

These findings emphasize the interconnectedness of climatic factors, agricultural practices, and emissions. Understanding these predictive relationships is essential for formulating policies that promote sustainable agriculture and environmental management.

Summary results of hypotheses: The analysis yielded mixed results for the hypothesized relationships between climatic, agricultural, and environmental factors and maize yield. Temperature was found to have no significant influence on maize yield in either the long run (p = 0.6122) or the short run, as indicated by the ARDL model. Rainfall demonstrated a significant negative short-term effect on maize yield (p = 0.0424), while its positive long-term effect was insignificant (p = 0.1792). Pesticide use significantly increased maize yield in both the long run (p = 0.0000) and the short run (p = 0.0095). CO_2 emissions per capita (CO_2PC) showed no significant short-term effect (p = 0.9292) but significantly increased maize yield in the long run (p = 0.0012). Agricultural CO_2 emissions (CO_2AG) exhibited significant mixed short-term effects, with positive impacts (p = 0.0047) and negative lagged impacts (p

= 0.0027), and a significant negative long-term impact on maize yield (p = 0.0001).

Granger causality tests supported several hypotheses. Temperature (p = 0.0065) and rainfall (p = 0.0118) were found to Granger-cause changes in maize yield, as did pesticide use (p = 0.0040). CO_2PC (p = 0.0228) and CO_2AG (p = 0.0116) were also found to Granger-cause changes in maize yield, with CO_2AG influencing maize yield through its relationship with CO_2PC. These findings underscore the complex interplay of climatic, agricultural, and environmental factors in influencing maize yield over time. These results provide comprehensive evidence on the roles of climatic and non-climatic factors in shaping maize yield through both direct impacts and causal relationships.

Stability and Diagnostics tests: Stability and diagnostics and tests are essential for validating model assumptions, detecting issues, assessing parameter stability, ensuring robustness, improving model specification, and avoiding invalid inferences. They are integral to credible and accurate econometric analysis, ensuring that findings and recommendations are based on sound and reliable models.

Table 12: Diagnostics and Stability Tests

Diagnostics	Statistics	p-value
Normality(J-B)	0.47	0.79
Serial Correlation $\chi^2(2)$	0.36	0.84
B-P-G Test (Scaled explained SS)	3.05	0.99
Ramsey RESET(F_{STAT})	0.10	0.7573
CUSUM Test	Stable	
CUSUM of Square Test	Stable	

The diagnostics and stability tests confirm the robustness and reliability of the ARDL model. The Jarque-Bera test for normality yields a statistic of 0.47 with a p-value of 0.79, indicating that the residuals are normally distributed; ensuring valid inferences (Figure 2). The Chi-square test for serial correlation shows no evidence of autocorrelation in the residuals (statistic: 0.36, p = 0.84), supporting the assumption of independent error terms. The Breusch-Pagan-Godfrey test for heteroskedasticity reports a statistic of 3.05 with a p-value of 0.99, confirming that the variance of the residuals is homoscedastic and consistent across observations. The Ramsey RESET test result (F-statistic: 0.10, p = 0.7573) indicates that the model is correctly specified without omitted variable bias. Furthermore, the CUSUM and CUSUM of Squares tests demonstrate stability over time, validating the reliability of the estimated coefficients. These results collectively affirm the model's adequacy for analyzing the complex relationships between climatic and non-climatic factors and maize yield.

This study explored the impact of climatic and non-climatic factors on maize yield in Nepal using an ARDL model. The results align with existing literature, though some differences highlight regional nuances. Rainfall had a significant short-term negative effect and an insignificant long-term positive effect on maize yield, which is consistent with *Baffour-Ata et al*. (2023), who also found short-term disruptions in crop yields due to rainfall variability. However, the positive long-term effect observed by Rowhani *et al*. (2011) contrasts with our findings, suggesting that Nepal's rain-fed agriculture is particularly vulnerable to rainfall fluctuations.

Temperature had no significant long-term impact, which aligns with Ghosh *et al.* (2023), who emphasized temperature extremes over gradual increases. This finding mirrors Harrison *et al.* (2011), indicating that temperature effects may not be significant in terms of average temperature changes. The positive influence of pesticide use on maize yield, found both in the long and short run, is consistent with Baig *et al.* (2023) and Chandio *et al*. (2023). However, the study highlights the need for sustainable pesticide practices to avoid long-term environmental harm.

The long-term positive effect of CO_2PC on maize yield aligns with Li and Tian (2024), but the negative effect of CO_2AG matches Gul *et al.* (2022), who identified the harmful impact of agricultural emissions on yields. Granger causality tests confirmed that rainfall, temperature, and CO_2 emissions Granger-cause maize yield, supporting findings by Chandio *et al.* (2022) and Guntukula and Goyari (2020). However, the lack of causality from agricultural emissions (CO_2AG) contrasts with Chandio *et al*. (2023).

This study corroborates many of the findings in the existing literature, such as the positive role of CO_2 emissions in boosting crop productivity, while also revealing the complex dynamics between climate change, pesticide use, and agricultural emissions in Nepal. The results underline the need for climate-resilient agricultural practices and sustainable pesticide use, emphasizing the importance of adapting to local environmental conditions to maintain long-term agricultural productivity.

Conclusion: This study reveals that rainfall, pesticide use, and CO_2 emissions significantly influence maize productivity in Nepal, with nuanced effects. Rainfall demonstrates mixed impacts, leading to short-term yield reductions but offering potential long-term benefits. Pesticide use consistently enhances productivity, while CO_2 emissions exhibit dual effects: per capita emissions (CO_2PC) improve yield in the long term, whereas agricultural emissions (CO_2AG) exert negative effects. These findings underscore the complex interplay between environmental factors and agrarian practices, highlighting the necessity for balanced strategies to sustain productivity. Policy implications include the promotion of sustainable pesticide use, the development of improved water management systems to address rainfall variability, and the mitigation of agricultural emissions through sustainable practices. This study applies ARDL and Granger causality tests to analyze the dual impact of CO_2 emissions, providing critical insights for Nepal's agricultural sector. Future research should investigate regional variations in climate impacts on maize yields to develop location-specific interventions.

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Data Availability: Data are available upon request from corresponding author.

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