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Impact of Climate Variability on Crop Productivity: Signal from Pooled OLS Regression

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Abstract

The study investigates the impact of climatic variability on major crop productivity, including paddy, wheat, maize, and millet in Nuwakot district, Nepal, using pooled OLS regression on the data span from 1990 to 2023. Descriptive analysis reveals that paddy has the highest mean yield (3.18 t/ha), followed by wheat (2.43 t/ha), maize (2.28 t/ha), and millet (1.3t/ha) millet productivity is positively skewed, representing occasional high yields, while other crops show more consistent patterns. Climate factors reveal moderate rainfall variability (414.1 mm), consistently high humidity (80.2%) and relatively stable temperatures (max 30.96 ^{0}C, min 21.58 ^{0}C).

OLS results shows that paddy productivity is significantly influenced by wheat yield (coef. = 0.966, p < 0.001) minimum temperature (coef. = 0.243, p = 0.017), while rainfall, humidity, and maximum temperature have weaker effects. Maize productivity is primarily affected by wheat productivity yields (coef. = 0.904, p < 0.001), while climatic factors showing no significant impact. millet shows low model fit (R^2 = 0.40), indicating limited influence of the variables considered. Temperature appears to be the key climatic determinant for paddy, whereas maize and millet are less climate sensitive.

Keywords: Agriculture, Climate variability, Crop Productivity, Humidity, OLS Regression, Rainfall, Temperature

Introduction

Agriculture in Nepal is highly vulnerable to climatic variations, which significantly influence crop productivity and food security. The central region, particularly Nuwakot district, presents a unique context for studying these impacts due to its diverse topography and microclimates. Understanding how climatic factors affect crop yields in this area is crucial for developing adaptive strategies to sustain agricultural productivity within changing environment conditions.

Many studies have showed the sensitivity of Nepalese agriculture to climatic changes. For instance, Malla (2008) noted that rising temperatures and altered precipitation patterns have led to reduced yields of staple crops like rice and maize. Similarly, Joshi et al. (2011) found that temperature increases have positively influenced rice yields, while rainfall variability has had mixed effects on other crops. Poudel and Kotani (2013) emphasized that the impacts of climatic factors vary across different altitudes and seasons, suggesting the need for localized adaptations strategies.

In the context of Nuwakot district, the interplay between climatic factors such as temperature, rainfall, humidity, and shoeshine hours is complex and not yet well understood. This study aims to fill this gap by employing a pooled Ordinary Least Square (OLS) regression model to analyze the effects of these climatic variables on crop yield productivity, including paddy, wheat, maize and millet, over the period from 1990 to 2023. These four crops play crucial role in Nepal's food security by supporting consumption across various regions and promoting sustainable agricultural livelihoods, particularly in mountainous rural areas. By focusing on this district, the research seeks to provide insights that can inform region-specific agricultural policies and practices, enhancing resilience to climate variability.

Materials and Methods

Data Source and Approach

This study utilized secondary data on climatic variables obtained from the Department of Hydrology and Meteorology (DHM), Nepal covering the period from 1990 to 2023. Crop yields data for the corresponding years were collected from national agricultural statistics reports to match the climatic records. Climatic factors included in the analysis were average temperature, total rainfall and relative humidity. The detail of climatic variables is given in table 1.

This study adopted a quantitative approach using a pooled OLS regression model to assess the impact of climatic factors on crop yield productivity. The analysis considered multiple crop types to generalize the findings and account for variations in climatic sensitivity among different crops.

Table 1

List of climatic variables

Variable	Measurement	Frequency	Adjustment
Rainfall	Mm	Monthly	Monsoon (JJAS) totals
Max. temperature	^{0}C	Daily	Annual Mean
Min. temperature	^{0}C	Daily	Annual Mean
Humidity	%	Monthly	Growing-season average

Statistical Analysis

Pooled OLS regression was applied to the panel dataset, combining cross-sectional (different crops) and time-series (1990 to 2023) observations. The pooled OLS model assumes that the relationship between crop yields and climatic factors is constant across time. The general model specification is;

$$Y_{it} = \beta_0 + \beta_1 Temp_{it} + \beta_2 Rainfall_{it} + \beta_3 Humidity_{it} + \epsilon_{it} \text{ --------- (1)}$$

Where, Y_{it} represents crops yields for crop i at time t, β_0 is intercept, β_i $(i = 1,2,3)$ is the coefficients of climatic factors and ϵ_{it} is error term.

All analyses were conducted using Python. Descriptive statistics were generated to summarize the data, model significance was evaluated using the F-test, and the explanatory power was assessed using R-squared values.

Results and Discussions

I. Descriptive Statistics

Table 2 illustrates the average crop yields (t/ha) and growing season. The analysis of average crop yields shows that paddy achieves the highest productivity, followed by wheat, maize, and Millet, reflecting differences in crop adaptability and management practices. Growing months varied among crops, with paddy and wheat requiring longer durations, which emphasizes the importance of aligning planting schedules with climatic conditions to optimize yields.

Table 2

Average crop yields and growing months

Crop	Scientific Name	Growing Months	Avg. Yield (t/ha)
Paddy	*Oryza sativa*	Jun-Nov	3.18
Wheat	*Triticum aestivum*	Nov-Apr	2.43
Maize	*Zea mays*	Mar-Sep	2.28
Millet	*Eleusine coracana*	Apr-Oct	1.3

Table 3

Descriptive statistics of study variables

Variables	**Mean**	**Sd**	**Min**	**25%**	**50%**	**75%**	**Max**	**Skewness**	**Kurtosis**
Paddy Productivity	3.18	0.88	1.51	2.38	3.03	4.04	4.7	-0.06	-1.1
Wheat Productivity	2.43	0.77	1.5	1.76	2.07	3.2	3.79	0.37	-1.47
Maize Productivity	2.28	0.75	1.43	1.61	2.04	3.05	3.78	0.49	-1.29
Millet Productivity	1.3	0.25	1.08	1.11	1.2	1.38	1.94	1.54	1.48
Rainfall	414.1	89.37	228.9	359.87	404.84	489.38	599.23	0.05	-0.39
Humidity	80.2	9.99	31.29	77.44	81.23	85.9	90.17	-3.69	17.81
Temp_Max	30.96	0.69	29.59	30.42	30.92	31.39	32.5	0.12	-0.38
Temp_Min.	21.58	0.73	19.5	21.34	21.8	22	22.72	-1.39	1.92

The descriptive statistics show that among the crops studied, paddy has the highest average productivity (3.18 t/ha), followed by wheat (2.43 t/ha), maize (2.28 t/ha), and millet (1.3 t/ha) (Table 3). millet productivity is positively skewed (1.54), indicating occasional higher yields, whereas paddy and wheat are nearly symmetric, suggesting more consistent yields. Most crops display negative kurtosis, reflecting relatively flat distributions with fewer extreme values, except Millet, which has a moderate positive kurtosis.

Regarding climatic factors, mean annual rainfall is 414.1 mm and fairly symmetric, indicating moderate variability across years. Humidity is high (80.2%) with strong negative skew and very high kurtosis, suggesting that most observations cluster near the upper range with few low values. Maximum temperature averages 30.96°C and minimum temperature 21.58°C, both showing low variability and near-symmetric distributions, indicating a relatively stable thermal range in Nuwakot district. Overall, these patterns suggest that crop yields are influenced by a generally stable temperature regime, moderate rainfall variation, and consistently high humidity, with certain crops like Millet experiencing occasional high productivity.

II. Correlation matrix of Crop with climatic factors

The correlation matrix highlights the relationships between crop yields and climatic factors, revealing how temperature, rainfall, humidity, and sunshine hours influence productivity (Figure 1). Understanding these correlations is significant as it identifies which climatic variables most strongly affect each crop, guiding farmers and policymakers in planning adaptive strategies. It also provides a basis for further regression analysis to quantify the magnitude and direction of these effects.

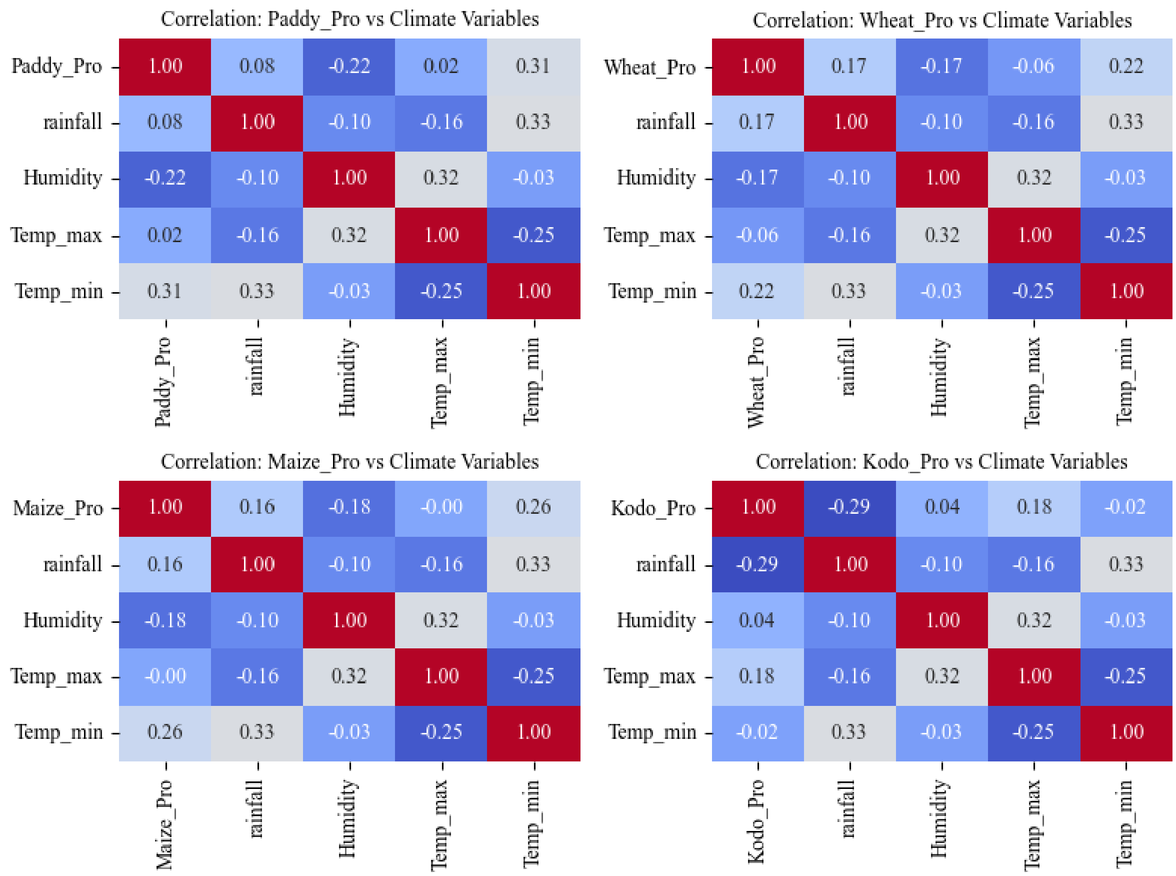

Figure 1. The correlation matrices of crop -climate relationships

According to figure 1, For paddy, minimum temperature and rainfall have moderate positive correlations with yield, while humidity shows a negative association. Wheat shows a weak positive link with minimum temperature but slight negative ties with humidity and maximum temperature. Maize productivity is weakly correlated with minimum temperature and rainfall, whereas humidity is negatively associated. In contrast, Millet has a negative correlation with rainfall, suggesting excess precipitation may reduce yield, while other climatic factors show only weak associations.

Overall, minimum temperature and rainfall appear more favorable for paddy and maize, while excessive rainfall is harmful for Millet, and wheat remains moderately sensitive to both temperature extremes and humidity.

III. Pooled OLS Regression

The pooled OLS regression is significant as it quantifies the impact of climatic variables on crop yields over time, capturing both cross-crop and temporal variations. Table 4-7 presents the pooled OLS regression for Paddy, Wheat, Maize, and Millet (Millet), respectively. It helps identify key determinants and informs evidence-based strategies for improving agricultural productivity under changing climatic conditions.

Table 4

Pooled OLS regression for paddy

Dep. Variable:	Paddy Productivity	R-squared:	0.906
Model:	OLS	Adj. R-squared:	0.880
Method:	Least Squares	F-statistic:	34.50
Date:	Fri, 15 June 2025	Prob (F-statistic):	2.61e-11
Time:	09:57:53	Log-Likelihood:	-2.9011
No. Observations:	33	AIC:	21.80
Df Residuals:	25	BIC:	33.77
Df Model:	7		

	Coef	std err	t	P>|t|	[0.025	0.975]
const	-7.7458	3.476	-2.229	0.035	-14.904	-0.587
Wheat_Pro	0.9657	0.263	3.667	0.001	0.423	1.508
Maize_Pro	0.0689	0.262	0.263	0.795	-0.471	0.608
Millet_Pro	0.0481	0.278	0.173	0.864	-0.524	0.620
rainfall	-0.0012	0.001	-1.726	0.097	-0.003	0.000
Humidity	-0.0100	0.006	-1.709	0.100	-0.022	0.002
Temp_max	0.1426	0.081	1.756	0.091	-0.025	0.310
Temp_min	0.2428	0.095	2.552	0.017	0.047	0.439

Omnibus:	1.883	Durbin-Watson:	1.624
Prob (Omnibus):	0.390	Jarque-Bera (JB):	0.994
Skew:	-0.400	Prob(JB):	0.608
Kurtosis:	3.288	Cond. No.	2.86e+04

The pooled OLS model explains a large portion of the variation in paddy productivity, with an R-squared of 0.906 and an adjusted R-squared of 0.880, indicating a strong overall fit. The F-statistic (34.50, $p < 0.001$) shows that the model is statistically significant (Table 4).
Among the predictors, wheat productivity (coef = 0.966, p = 0.001) and minimum temperature (coef = 0.243, p = 0.017) have significant positive effects on paddy yield, suggesting that higher wheat yields and warmer nights are associated with increased paddy productivity. Maximum temperature shows a positive but marginal effect (coef = 0.143, p = 0.091). Rainfall (coef = -0.0012, p = 0.097) and humidity (coef = -0.010, p = 0.100) have negative but marginally insignificant effects, while maize and Millet productivity have no

significant impact. Overall, temperature appears to be a key climatic factor influencing paddy yield in Nuwakot, while other climatic variables show weaker associations.

Table 5

Pooled OLS regression for Wheat

Dep. Variable:	Wheat Productivity	R-squared:	0.953
Model:	OLS	Adj. R-squared:	0.939
Method:	Least Squares	F-statistic:	71.93
Date:	Fri, 15 June 2025	Prob (F-statistic):	5.61e-15
Time:	10:00:11	Log-Likelihood:	13.279
No. Observations:	33	AIC:	-10.56
Df Residuals:	25	BIC:	1.414
Df Model:	7		

	coef	std err	t	P>|t|	[0.025	0.975]
const	5.0720	2.098	2.417	0.023	0.751	9.393
Maize_Pro	0.5829	0.110	5.276	0.000	0.355	0.810
Millet_Pro	0.1675	0.167	1.003	0.325	-0.176	0.511
Paddy_Pro	0.3622	0.099	3.667	0.001	0.159	0.566
Humidity	0.0046	0.004	1.261	0.219	-0.003	0.012
Temp_max	-0.1038	0.048	-2.142	0.042	-0.204	-0.004
Temp_min	-0.1302	0.060	-2.169	0.040	-0.254	-0.007

Omnibus:	0.280	Durbin-Watson:	1.749
Prob(Omnibus):	0.869	Jarque-Bera (JB):	0.013
Skew:	-0.049	Prob(JB):	0.993
Kurtosis:	3.012	Cond. No.	2.81e+04

The OLS model explains 95.3% of the variation in wheat productivity (Adj. $R^2 = 0.939$, $F = 71.93$, $p < 0.001$), indicating a strong and statistically robust fit (Table 5). While humidity shows a positive but insignificant effect ($\beta = 0.0046$, $p = 0.219$), both maximum temperature ($\beta = -0.1038$, $p = 0.042$) and minimum temperature ($\beta = -0.1302$, $p = 0.040$) exert significant negative influences, suggesting that elevated daytime and nighttime temperatures reduce yield, likely via heat stress and shortened grain-filling periods. Model diagnostics confirm normality ($p > 0.86$) and minimal autocorrelation (DW = 1.749), though the high condition number (2.81×10^4) signals potential multicollinearity. These results emphasize temperature regulation as a critical factor for maintaining wheat productivity under warming climatic conditions.

Table 6

Pooled OLS regression for Maize

Dep. Variable:	Maize_Pro	R-squared:	0.925
Model:	OLS	Adj. R-squared:	0.904
Method:	Least Squares	F-statistic:	44.00
Date:	Fri, 15 June 2025	Prob (F-statistic):	1.69e-12
Time:	10:00:11	Log-Likelihood:	6.0429
No. Observations:	33	AIC:	3.914
Df Residuals:	25	BIC:	15.89
Df Model:	7		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-3.6829	2.807	-1.312	0.201	-9.464	2.098
Wheat_Pro	0.9038	0.171	5.276	0.000	0.551	1.257
Millet_Pro	-0.0907	0.211	-0.429	0.671	-0.526	0.344
Paddy_Pro	0.0400	0.152	0.263	0.795	-0.274	0.354
rainfall	-0.0002	0.001	-0.326	0.747	-0.001	0.001
Humidity	-0.0027	0.005	-0.576	0.570	-0.012	0.007
Temp_max	0.0759	0.064	1.188	0.246	-0.056	0.207
Temp_min	0.0787	0.080	0.985	0.334	-0.086	0.243

Omnibus:	1.397	Durbin-Watson:	1.692
Prob(Omnibus):	0.497	Jarque-Bera (JB):	0.602
Skew:	-0.297	Prob(JB):	0.740
Kurtosis:	3.294	Cond. No.	3.02e+04

The pooled OLS model explains a high proportion of the variation in maize productivity, with an R-squared of 0.925 and an adjusted R-squared of 0.904, indicating a strong model fit. The F-statistic (44.00, $p < 0.001$) confirms that the overall regression is statistically significant (Table 6). Among the predictors, only wheat productivity has a significant positive effect on maize yield (coef = 0.904, $p < 0.001$), suggesting that higher wheat yields are associated with increased maize productivity. Other variables, including paddy and Millet productivity, rainfall, humidity, and maximum and minimum temperatures, show no significant impact on maize yield. This indicates that, in Nuwakot, maize productivity is primarily influenced by the performance of wheat rather than direct climatic factors.

Table 7

Pooled OLS regression for Millet

Dep. Variable:	Millet_Pro	R-squared:	0.400
Model:	OLS	Adj. R-squared:	0.231
Method:	Least Squares	F-statistic:	2.377
Date:	Fri, 15 June 2025	Prob (F-statistic):	0.0523
Time:	10:00:11	Log-Likelihood:	7.9739
No. Observations:	33	AIC:	0.05211
Df Residuals:	25	BIC:	12.02
Df Model:	7		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.4727	2.735	-0.173	0.864	-6.106	5.161
Wheat_Pro	0.2310	0.230	1.003	0.325	-0.243	0.705
Maize_Pro	-0.0807	0.188	-0.429	0.671	-0.468	0.306
Paddy_Pro	0.0249	0.144	0.173	0.864	-0.271	0.321
rainfall	-0.0010	0.000	-1.986	0.058	-0.002	3.67e-05
Humidity	0.0014	0.004	0.317	0.754	-0.008	0.010
Temp_max	0.0477	0.061	0.780	0.443	-0.078	0.174
Temp_min	0.0063	0.077	0.082	0.936	-0.152	0.165

Omnibus:	3.850	Durbin-Watson:	1.422
Prob(Omnibus):	0.146	Jarque-Bera (JB):	2.640
Skew:	0.670	Prob(JB):	0.267
Kurtosis:	3.350	Cond. No.	3.13e+04

The pooled OLS model explains a modest portion of the variation in Millet productivity, with an R-squared of 0.400 and an adjusted R-squared of 0.231, indicating a relatively weak model fit. The F-statistic (2.377, p = 0.052) suggests that the overall regression is marginally insignificant at the 5% level (Table 7).

None of the explanatory variables have a statistically significant impact on Millet productivity. Rainfall shows a marginal negative effect (coef = -0.001, p = 0.058), indicating a potential slight decrease in Millet yield with higher rainfall, but this effect is not statistically strong. Other factors, including wheat, maize, and paddy productivity, humidity, and temperatures, show no significant influence. This suggests that Millet yield in Nuwakot is largely unaffected by the climatic factors and crop interactions considered in this model.

IV. Actual and Predicted Corp Productivity, Residual and climatic impacts

Comparing actual and predicted crop productivity demonstrates the robustness of the pooled OLS model in reflecting real-world crop-climate dynamics. Figure 2-3 illustrate the trends of climatic factors with predicted crop productivity, residuals and the contribution of climatic factors on crop productivity, respectively. Analysis of residuals reveals subtle deviations, highlighting areas where additional factors may influence yields. Understanding these impacts provides critical insights for devising climate-adaptive strategies to optimize crop performance in Nuwakot district.

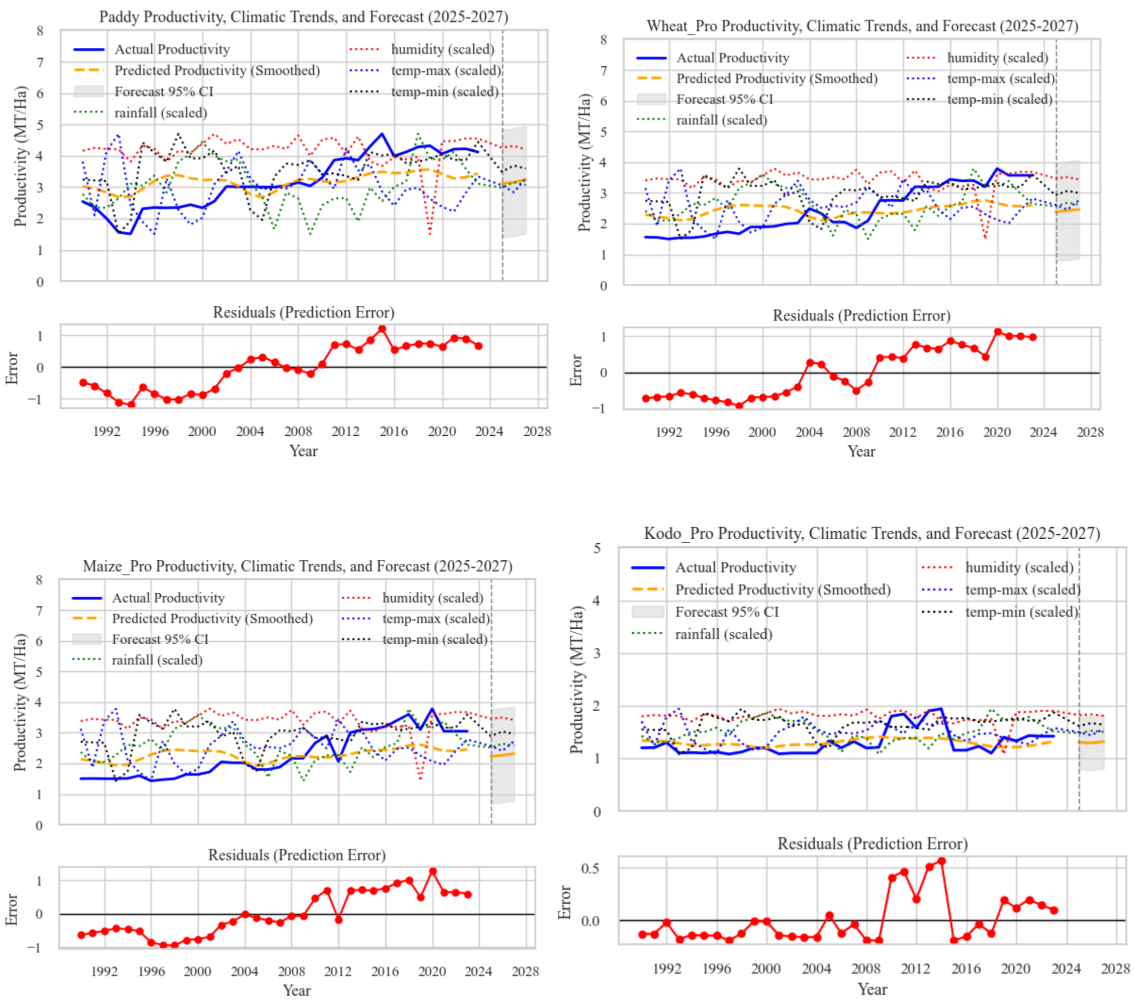

Figure 2. Trends of climatic factors with predicted crop productivity and residuals

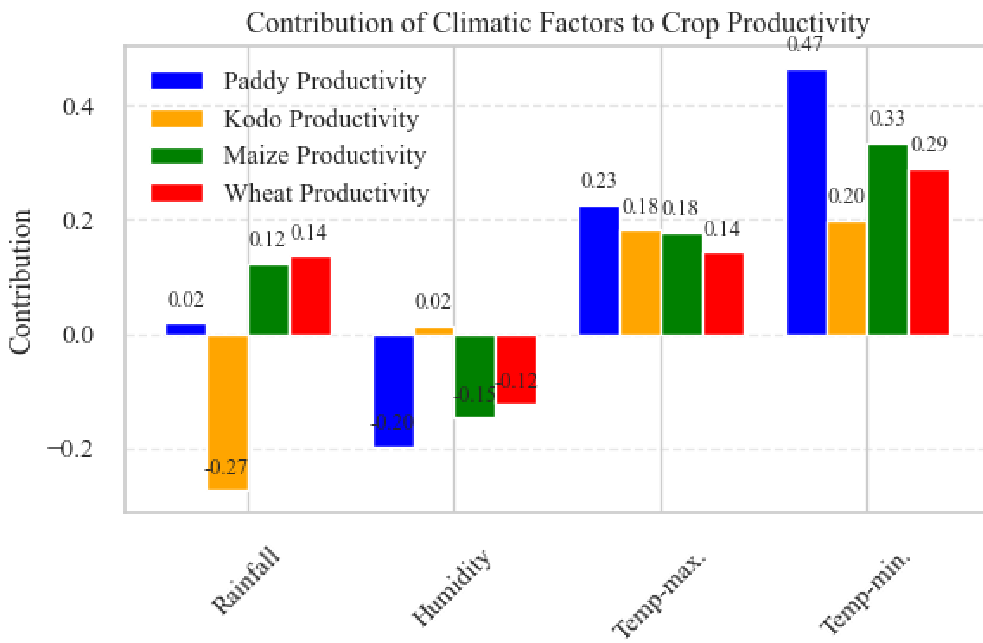

Figure 3. Contribution of climatic factors on crop productivity

Discussion

This study shows that climatic factors play a direct role in shaping paddy yields in hilly region. The positive link between minimum temperature and yield suggests that moderate night-time warming may support processes like respiration and grain filling in rice (Ray et al., 2015). On the other hand, the slight negative effect of rainfall and humidity, though not statistically strong, points to possible risks such as higher disease incidence or reduced soil aeration when excess moisture is present (Joshi et al., 2011).

The results also vary across regions. Warmer conditions may benefit high-altitude areas where cold limits growth, while lowland regions could face yield loss from heat stress (Poudel & Kotani, 2013). This makes local adaptation important, for example, through the use of flood- or heat-tolerant rice varieties and better timing of planting (Gautam et al., 2025).

The pooled OLS regression proved useful in examining these crop–climate relationships, providing a foundation for future use of more advanced models like panel data or machine learning approaches (Ray et al., 2015). Overall, the findings confirm that temperature, rainfall, and humidity strongly affect rice productivity. Excessive heat during flowering can reduce grain formation (Pandey et al., 2020), while both drought and waterlogging linked to rainfall extremes can suppress yields (Shrestha et al., 2019). Humidity also contributes to fungal diseases that reduce output (Gautam & Thapa, 2021). These outcomes are consistent with earlier studies showing how delayed monsoons and erratic rainfall reduce production in the Terai and mid-hill regions (Adhikari et al., 2018). The results point to the need for practical solutions, including climate-resilient rice varieties, efficient irrigation, and drainage systems to help stabilize paddy yields under shifting weather patterns.

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Conflict of Interest

Authors declare that there is no conflict of interest

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