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Climate Change and its Adaptation in Agricultural Sector

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Abstract

Background: Climate change has emerged as a significant threat to global agricultural productivity, affecting food security and economic stability, particularly in agrarian economies. The agricultural sector is highly vulnerable to climate variations, including changes in temperature, precipitation patterns, and the frequency of extreme weather events. Understanding how these climatic factors influence agricultural output is crucial for developing effective adaptation strategies.

Objective: The study assesses the relationship between climate change on agricultural productivity and to identify effective adaptation strategies that can mitigate the adverse effects of changing climatic conditions on agriculture.

Methods: This study utilizes a variety of secondary data sources. In this study quantitative modeling of climate change and its adaptation in agricultural sector is conducted by considering the time period of 32 years from 1991 to 2022 using the autoregressive distributed lag approach (ARDL) followed by TY Non-Granger Causality Test.

Results: The analysis shows that annual average maximum temperature boosts agricultural productivity in the long run, supported by positive irrigation effects. Conversely, minimum temperature negatively impacts crop growth over time. CO2 emissions and precipitation are insignificant in the long run but have short-term effects. Surprisingly, chemical fertilizers reduce productivity, while improved seeds only enhance it in the short term. Irrigation has a small positive long-term effect.

Conclusion: The study reveals that the annual average maximum temperature boosts agricultural productivity in the long run due to farmers' adaptation strategies, while minimum temperature negatively impacts crop growth. CO2 emissions and precipitation show no significant long-term effects, though they have short-term impacts. Chemical fertilizers reduce productivity over time, likely due to soil degradation, while irrigation has a marginally positive long-term effect. Improved seeds enhance short-term productivity but show no significant long-term impact

Implication: The study highlights the need for sustainable practices and holistic to address both immediate and long-term agricultural challenges posed by climate change approaches for boosting agricultural output

Keywords: Climate change, Agriculture sector, Time series, ARDL model

JEL Classification: C32, Q1, Q5

Introduction

Nepal's diverse topography is characterized by distinct agricultural zones, including plains, hills, mid-hills, high hills, and mountains. These zones each support specific cropping patterns that are adapted to their unique climatic conditions (Krupnik et al., 2021). Climate change is an ongoing global phenomenon characterized by long term alterations in the temperature, precipitation patterns, and other climatic factors. The Intergovernmental Panel on Climate Change (IPCC) has documented substantial evidence of climate change highlighting rising global temperatures, shifting weather patterns, and increasing frequency of extreme weather events (IPCC, 2021) and previously also projected that by 2050 in East and Southeast Asia, crop yields could increase up to 20% while it could decrease by up to 30% in Central and South Asia (Kumar & Singh, 2014; Devkota & Phuyal, 2015) .

Climate change acts as both a stressor and risk multiplier (Gitz & Meybeck, 2012) leading to increased crop failures (Kim & Mendelsohn, 2023) and extreme weather events (Newman & Noy, 2023). Farmers face higher temperatures that stress crops and livestock and make agriculture labor more difficult and dangerous (USAID, 2022). Nepalese farmers are also experiencing unpredictable weather patterns, increased frequency of extreme weather events, and shifting agricultural zones, which threaten their livelihoods and food security (Gentle & Maraseni, 2012; Krishnamurthy et al., 2013; Poudel et al., 2017).

The impact of climate change on agriculture can be understood directly as agro sector is more dependent on natural nurture. This concern is equally applicable to Nepal too as early symptoms of climate cruelty and alarmingly increased temperature have been observed almost in double pace within a shorter time horizon compared to global temperature rise (Acharya & Bhatta, 2013).

Agriculture is a critical sector that supports livelihoods and ensures food security for billions of people worldwide. This sector is considered to be the backbone of Nepalese economy and contributes 24% of GDP and approximately 62% of household's main occupation is agriculture (MoF, 2023). It is intrinsically linked to climate conditions, making it vulnerable to climate change. Temperature, precipitation and co2 level directly affect crop growth, water availability, soil health and pest and disease dynamics (Lobell & Field, 2007).

In the highest altitudes, population depends entirely on agriculture for their livelihood and extreme climatic conditions will economically stress these areas by affecting agricultural production and food security (Pokhrel & Thapa, 2005). Climate change is leading to longer growing seasons in many regions, which can have both positive and negative effects on agricultural productivity. On the positive side, a longer growing season extends the period during which crops can be cultivated (Hakala et al., 2011). This allows farmers to plant crops that require a longer time to mature and even potentially harvest more than one crop cycle per year. This diversification in crop cultivation can enhance agricultural productivity and profitability, contributing positively to local economies and food security. Additionally, prolonged growing seasons may result in the proliferation of pests and diseases that thrive in warmer climates, increasing the need for pest control measures and raising production costs

Plant development relies significantly on both high and low temperatures (Atkinson & Porter, 1996). Crops have particular temperature thresholds that are conducive to their growth and reproduction (Parker et al., 2020). When temperatures rise within this optimal range, crops can benefit significantly. Excessively high temperatures can also affect the quality of the production. Crops that are subjected to heat stress may develop smaller fruits, lower nutritional value, and poorer storage qualities (Moretti et al., 2010). This not only affects the marketability of the produce but also its suitability for consumption and processing. Conversely, increased minimum temperatures can negatively impact crops by altering metabolic processes and increasing respiration rates, leading to lower net productivity (Hatfield et al., 2011). Thus, the relationship between temperature and crop productivity is a double-edged sword (Yan et al., 2024). The key to managing these risks lies in understanding the specific temperature requirements of each crop and implementing adaptive strategies to mitigate the adverse effects of excessive heat. This may include developing heat-tolerant crop varieties, optimizing irrigation practices, and adopting agronomic techniques that enhance crop resilience to temperature extremes (Govindaraj et al., 2018; Ahmed et al., 2019).

Precipitation patterns are equally important for agriculture, influencing water availability for crops. Both excessive and insufficient rainfall can adversely affect crop yields (Ogenga et al., 2018; Li et al., 2019). While adequate precipitation is essential for crop growth, extreme weather events such as droughts and floods can lead to crop damage and loss. Changes in precipitation patterns due to climate change are expected to exacerbate these challenges, making water management a critical aspect of agricultural adaptation (Nelson et al., 2009).

In this regard, this paper aims to explore the short-term and long-term impacts of variations in temperature, precipitation, and CO2 emissions on agricultural productivity. Additionally, it seeks to examine the influence of agricultural inputs, including improved seeds, irrigation, and chemical fertilizers, in shaping agricultural productivity within the context of changing climatic conditions.

The structure of the study is as follows: Section two provides a review of relevant literature, while section three outlines the methodology used in the research. Section four presents the results along with their discussion, and section five offers the study's conclusions.

Literature Review

Several studies have projected the adverse impacts of climate change on agricultural production, particularly for tropical commodities. The study of (Kandel et al., 2024) investigated the role of adaptation strategies in mitigating food insecurity among smallholder farm households in Nepal under climate change extremes. Using data from 400 households across the Mountains, Hills, and Terai regions, the study found that 12% of households were food insecure, while 22% relied on short-term coping strategies. Results from ordered logit models revealed that drought negatively impacts food security, while adaptive measures like irrigation, agroforestry, and temporary migration improve it. The research also emphasized the importance of education, market access, credit, and information in enhancing farmers' adaptive capacity. The study recommends tailoring adaptation strategies to the socio-economic and institutional contexts of each agro-ecological zone. Nelson et al. (2009) argued climate change is expected to have both positive and negative effects on crop production and yields, leading to significant benefits or challenges for agriculture. Higher temperatures are likely to reduce crop yields and exacerbate the spread of weeds and pests, posing a substantial threat to agricultural productivity. Additionally, changes in precipitation patterns may increase the risk of short-term crop failures and contribute to long-term declines in agricultural output.

Schroth et al. (2017) used site-level to inform regional adaptation planning, revealing projected losses in cacao production in West Africa. Similarly, Bunn et al. (2015) examined the global impacts of climate change on Arabica coffee production, with both studies concluding that these production losses pose significant threats to national economies and the regional and global supply chains reliant on cocoa and coffee. Knox et al. (2012) studied climate change effects on agriculture in South Asia and Africa, projecting that major grain crops like wheat, maize, and sorghum could experience production losses of up to 8% by 2050, with Africa seeing a 17% reduction. The study highlighted that these losses threaten crop yields in regions already facing food insecurity. In India, Auffhammer et al. (2012) reported that climate-induced monsoon disruptions from 1966 to 2002 led to a 4% reduction in rice yields. Other researchers, including (Morton, 2007; Harvey et al., 2014; Ayanlade et al., 2017; Kreft et al., 2017), have projected that climate change will significantly impact local, national, and global industries. However, they emphasize that marginalized and impoverished communities in developing countries, which depend on small-scale agriculture, will be the most vulnerable.

In Nepalese context, Charoenratana and Kharel (2024) examined the impacts of climate change on rainfall, temperature, and agricultural productivity using data from 110 household surveys, focus groups, and interviews. The study highlights increased household vulnerability due to declining productivity and emphasizes the need for efficient farm and livestock management. It provides insights into Nepalese farmers' adaptation strategies and their correlation with local government roles. The findings suggest practical policies to enhance farmers' resilience to climate change at the local level. Rayamajhee et al. (2021), examined the effects of climate change on rice production in Nepal using NLSS panel data from 2003 and 2010. The study found that a 1°C rise in average summer temperature significantly reduces rice yields by 4,183 kg, while extreme temperature days had no direct impact. Extreme rainfall variations negatively affected productivity, though average monsoon rainfall did not. Despite climate challenges, districts with better road and river access showed higher technical efficiency, highlighting the importance of improved irrigation and market access for adaptation. Another study in Nepalese context conducted by Bista et al. (2021) revealed that, developing countries, including Nepal, face greater vulnerability due to lower adaptive capacities, with low-income groups disproportionately affected. Vulnerability varies by income level and is higher in lower-altitude regions. The research highlights that climate change poses a significant threat to Nepal's low-income populations and agricultural sectors, where costs outweigh potential benefits from production.

Existing literature often emphasizes the negative effects of climate change on agriculture, such as rising temperatures, erratic precipitation, and increasing CO2 levels. However, this approach oversimplifies findings across diverse regions and crops. The observed short-term positive impact of maximum temperature and CO2 emissions reveals a gap in understanding the complex and sometimes contradictory effects of climate variables on agriculture.

Research Methodology

This paper estimates the short- and long-term impacts of climate change and adaptation in Nepal's agriculture sector using the Auto Regressive Distributed Lag (ARDL) model, based on time series data from 1991 to 2022. Agricultural productivity (% of GDP) is the dependent variable, with data sourced from the World Development Indicators (WDI). Independent climatic variables annual average maximum and minimum temperatures (°C) and precipitation (mm) were obtained from Nepal's Department of Hydrology and Meteorology. CO2 emission data (kt) were also sourced from WDI, while agricultural inputs, representing adaptation measures such as irrigation (hectares), chemical fertilizers, and improved seeds (metric tons), were extracted from the Economic Survey published by Nepal's Ministry of Finance.

Econometric Model

This study used the following economic functions to determine the interaction between agriculture, climatic factors, and agriculture inputs as an adaptation.

LAGR=f(LMAT, LMIT, LPREC, LCO2, LIMPS, LFERT, LIRRIG)

The next equation presents the empirical model

$$LAGR=\alpha_0+\beta_1 LMAT+\beta_2 LMIT+\beta_3 LPREC+\beta_4 LCO2+\beta_5 LIMPS+\beta_6 LFERT+\beta_7 LIRRIG \quad (1)$$

Further, the above equation can be expanded as the econometric model in the following form:

$$LAGR=\alpha_0+\beta_1 LMAT+\beta_2 LMIT+\beta_3 LPREC+\beta_4 LCO2+\beta_5 LIMPS+\beta_6 LFERT+\beta_7 LIRRIG+u_t \quad (2)$$

where,

LAGR = logarithm form of agriculture

LMAT = logarithm form of average maximum temperature

LMIT = logarithm form of average minimum temperature

LPREC = logarithm form of precipitation

LCO2 = logarithm form of co2 emission

LIMPS = logarithm form of improved seeds

LFERT = logarithm form of chemical fertilizer

LIRRIG = logarithm form of irrigation

Unit Root Testing

Before analyzing time series data, it is crucial to determine its stationarity. Failing to do so can lead to misleading results, known as spurious regression. The statistical test used to check for stationarity is called a unit root test. A stationary series is integrated at level, denoted as I(0), while a non-stationary series can become stationary by differencing. If stationarity is achieved after the first difference, the series is integrated at the first order, or I(1). If it requires differencing twice, it is considered integrated at the second order, or I(2).

Bounds test of co-integration

If the data series are integrated at different levels some, being I(0) and others I(1) the autoregressive distributed lag (ARDL) model should be applied according to (Pesaran & Shin, 1995) due to its several significant advantages. Unlike traditional cointegration methods like the Engel-Granger and Johansen-Juselius tests, which require variables to be integrated of the same order, ARDL can be applied regardless of whether variables are integrated of order I(0), I(1), or a combination of both (Jalil & Rao, 2019) and also ARDL uses a single-equation approach, it simplifies the estimation process, especially when compared to more complex multivariate systems such as Johansen's cointegration method. This flexibility makes ARDL particularly useful in empirical research. A key feature of ARDL is the ability to assign different optimal lag lengths to each variable, ensuring that the model captures the specific dynamics of each variable more effectively. This flexibility in lag structure improves model accuracy by addressing important lag effects that might otherwise be overlooked. ARDL also handles the issue of endogeneity better than many traditional models because it includes lagged values of both dependent and independent variables, reducing the bias associated with endogenous regressors (McCann et al., 2010).

Additionally, ARDL can detect cointegration even in non-stationary time series data, using the Bound Testing approach to confirm the existence of long-run relationships despite potential stationarity issues. Another advantage is that from the ARDL model, an error correction model (ECM) can be derived, which captures both short-run and long-run dynamics within a single framework, making the interpretation of results more straightforward. Furthermore, by allowing different lag structures for different variables, ARDL minimizes serial correlation in the residuals, thus improving the robustness of the model and ensuring that the estimates are consistent and reliable. Overall, ARDL stands out as a highly flexible and efficient model, ideal for small samples, non-stationary data, and dealing with endogeneity, making it a widely recommended choice for econometric analysis. Since, the data series employed in this paper are integrated at different levels. Hence, it is necessary to conduct ARDL cointegration test as follow:

$$\begin{aligned}\Delta LAGR_t = \alpha_0 &+ \sum_{i=0}^{p}\beta_i \Delta LAGR_{t-i} + \sum_{j=0}^{q}\beta_j \Delta LMAT_{t-j} + \sum_{k=0}^{r}\beta_k \Delta LMIT_{t-k} + \sum_{l=0}^{s}\beta_l \Delta LPREC_{t-l} + \sum_{m=0}^{t}\beta_m \Delta LCO2_{t-m} \\ &+ \sum_{n=0}^{u}\beta_n \Delta LIMPS_{t-n} + \sum_{o=0}^{v}\beta_o \Delta LFERT_{t-o} + \sum_{p=0}^{w}\beta_p \Delta LIRRIG_{t-p} + \lambda_{AGR} LAGR_{t-1} \\ &+ \lambda_{MAT} LMAT_{t-1} + \lambda_{MIT} LMIT_{t-1} + \lambda_{PREC} PREC_{t-1} + \lambda_{CO2} LCO2_{t-1} + \lambda_{IMPS} LIMPS_{t-1} \\ &+ \lambda_{FERT} LFERT_{t-1} + \lambda_{IRRIG} LIRRIG_{t-1} \\ &+ \varepsilon_t \end{aligned} \quad (3)$$

In equation (3) , Δ represent short run parameters and ε_t is the error term.

Technically, an F-test is performed to test the null hypothesis $\delta_{LAGR} = \delta_{LMAT} = \delta_{LMIT} = \delta_{LPREC} = \delta_{LCO2} = \delta_{LIMPS} = \delta_{LFERT} = \delta_{LIRRIG} = 0$ against the alternative hypothesis $\delta_{LAGR} \neq \delta_{LMAT} \neq \delta_{LMIT} \neq \delta_{LPREC} \neq \delta_{LCO2} \neq \delta_{LIMPS} \neq \delta_{LFERT} \neq \delta_{LIRRIG} = 0$. The null hypothesis posits that there is no long-run relationship among the variables. If we fail to reject the null hypothesis, it indicates that no long-run relationship exists among the variables. Conversely, rejecting the null hypothesis suggests a long-run relationship is present. It is important to note that the conventional F-statistic is used because the distribution is nonstandard and even asymptotic (Jalil & Rao, 2019). Therefore, (Pesaran et al., 2001) provided critical values for I(0) and I(1) at different significance levels. If the calculated F-statistic is below the critical value for I(0), there is no cointegration. If the F-statistic exceeds the critical value for I(1), a long-run relationship exists. If the calculated F-statistic falls between the critical values for I(0) and I(1), no definitive conclusion about cointegration can be made.

Once the co-integration is identified, ARDL framework can be used to estimate the elasticities of both long run and short run coefficients using equation (4) and (5).

$$\begin{aligned} LAGR = \alpha_0 &+ \sum_{i=1}^{p} \varphi_i LAGR_{t-i} \\ &+ \sum_{j=1}^{q} \varphi_j LMAT_{t-j} + \sum_{k=1}^{r} \varphi_k LMIT_{t-k} + \sum_{l=1}^{s} \varphi_l LPREC_{t-l} + \sum_{m=1}^{t} \varphi_m LCO2_{t-m} \\ &+ \sum_{n=1}^{u} \varphi_n LIMPS_{t-n} + \sum_{o=1}^{v} \varphi_o LFERT_{t-o} + \sum_{p=1}^{w} \varphi_p LIRRIG_{t-p} + \mu_t \end{aligned} \tag{4}$$

$$\begin{aligned} \Delta LAGR = \gamma_0 &+ \sum_{i=1}^{p} \gamma_i \Delta LAGR_{t-i} \\ &+ \sum_{j=1}^{q} \gamma_j \Delta LMAT_{t-j} + \sum_{k=1}^{r} \gamma_k \Delta LMIT_{t-k} + \sum_{l=1}^{s} \gamma_l \Delta LPREC_{t-l} + \sum_{m=1}^{t} \gamma_m \Delta LCO2_{t-m} \\ &+ \sum_{n=1}^{u} \gamma_n \Delta LIMPS_{t-n} + \sum_{o=1}^{v} \gamma_o \Delta LFERT_{t-o} + \sum_{p=1}^{w} \gamma_p \Delta LIRRIG_{t-p} + \psi ECT_{t-1} \\ &+ \mu_t \end{aligned} \tag{5}$$

Where, ECT_{t-1} indicates the error correction term, which must be negative and the value of its coefficient must lie between 0 and 1. From equations (4) and (5), both the short-run and long-run elasticity can be estimated, respectively. The negative sign of error correction implied the system stability to revert back to its normal position after a short-run shock.

TY Granger non-causality test

This study used the Toda-Yamamoto (TY) technique to conduct a Granger causality test that remains valid regardless of whether the time series are integrated at levels I(0), first differences I(1), or even second differences I(2). Traditional cointegration tests can be sensitive to the selection of lags and the exclusion of relevant variables, potentially introducing bias. By utilizing an augmented VAR model, the TY method applies a Wald test statistic, which follows an asymptotic chi-square distribution irrespective of the integration order or cointegration properties of the variables. The modified Wald test imposes restrictions on the parameters of the VAR(k), where k represents the chosen lag length of the system. The fundamental idea behind the TY approach is to augment the correct lag order k with the maximum order of integration, denoted as d_{max}.

Equation (6) below shows the estimated relationship based on the TY test.

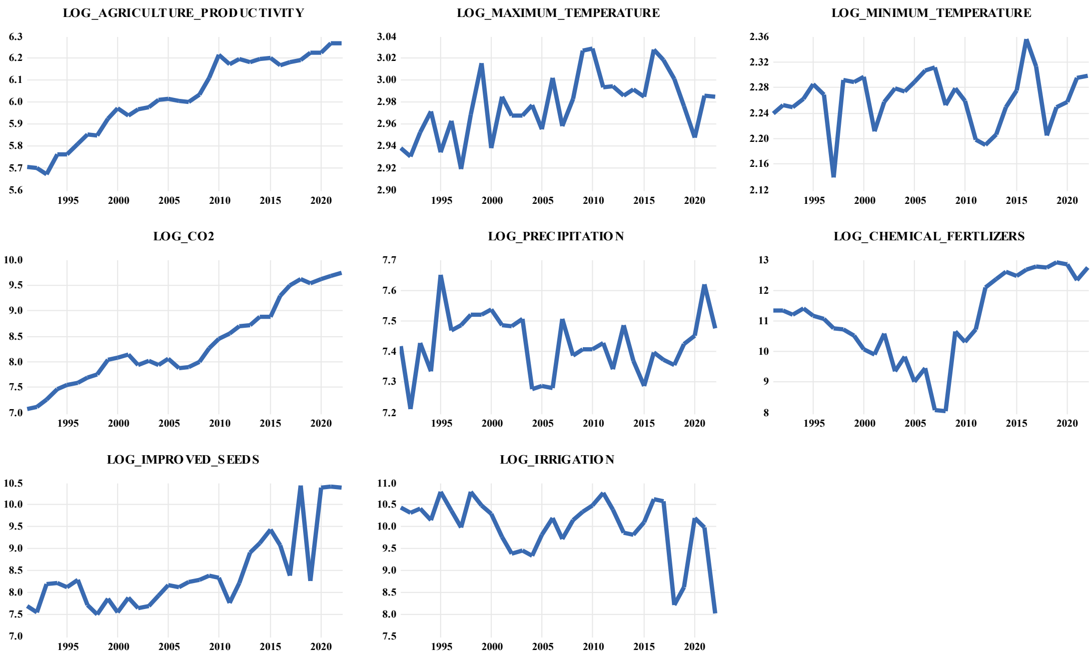
$$\begin{bmatrix} LAGR_t \\ LMAT_t \\ LMIT_t \\ LPREC_t \\ LCO2_t \\ LIMPS_t \\ LFERT_t \\ LIRRIG_t \end{bmatrix} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \beta_4 \\ \beta_5 \\ \beta_6 \\ \beta_7 \\ \beta_8 \end{bmatrix} + \begin{bmatrix} A_{11,1} & A_{12,1} & \cdots & A_{18,1} \\ A_{21,1} & A_{22,1} & \cdots & A_{28,1} \\ \vdots & \vdots & \ddots & \vdots \\ A_{81,1} & A_{82,1} & \cdots & A_{88,1} \end{bmatrix} + \begin{bmatrix} LAGR_{t-1} \\ LMAT_{t-1} \\ LMIT_{t-1} \\ LPREC_{t-1} \\ LCO2_{t-1} \\ LIMPS_{t-1} \\ LFERT_{t-1} \\ LIRRIG_{t-1} \end{bmatrix} + \cdots +$$

$$\begin{bmatrix} A_{11,k} & A_{12,k} & \cdots & A_{18,k} \\ A_{21,k} & A_{22,k} & \cdots & A_{28,k} \\ \vdots & \vdots & \ddots & \vdots \\ A_{81,k} & A_{82,k} & \cdots & A_{88,k} \end{bmatrix} + \begin{bmatrix} LAGR_{t-k} \\ LMAT_{t-k} \\ LMIT_{t-k} \\ LPREC_{t-k} \\ LCO2_{t-k} \\ LIMPS_{t-k} \\ LFERT_{t-k} \\ LIRRIG_{t-k} \end{bmatrix} + \begin{bmatrix} A_{11,p} & A_{12,p} & \cdots & A_{18,p} \\ A_{21,p} & A_{22,p} & \cdots & A_{28,p} \\ \vdots & \vdots & \ddots & \vdots \\ A_{81,p} & A_{82,p} & \cdots & A_{88,p} \end{bmatrix} \begin{bmatrix} LAGR_{t-k} \\ LMAT_{t-k} \\ LMIT_{t-k} \\ LPREC_{t-k} \\ LCO2_{t-k} \\ LIMPS_{t-k} \\ LFERT_{t-k} \\ LIRRIG_{t-k} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \\ \varepsilon_{5t} \\ \varepsilon_{6t} \\ \varepsilon_{7t} \\ \varepsilon_{8t} \end{bmatrix} \tag{6}$$

Data Visualization

For visualization of time series data, time series plots are commonly used. Time series plots of the variables used in this paper are presented in figure 1.

Figure 1: Data Series used in the study



The agricultural productivity graph shows a long-term positive trend, with rapid growth around 2010, likely due to improved farming practices and climate adaptation. In contrast, maximum temperatures fluctuate more, peaking between 2010 and 2016, possibly reflecting global warming, followed by a cooling phase around 2018, and a slight rise toward 2020-2022, though not as high as earlier levels. Minimum temperatures remained stable until a sharp drop in 1995, then recovered, with a significant rise peaking in 2014, followed by a decline around 2016 and another rise by 2020-2022. CO2 emissions consistently increased, with steady growth in the 1990s and early 2000s, a sharper rise from the mid-2000s, and a spike around 2013-2014 due to industrial expansion, continuing at a moderated pace through 2022. Precipitation exhibited notable variability, peaking in the early 1990s, stabilizing through the mid-1990s to early 2000s, and then fluctuating more from the mid-2000s onward, peaking in 2021 before a slight decline in 2022.

Chemical fertilizer usage initially declined until 2007, followed by a sharp dip and a rapid recovery peaking in 2013, stabilizing at higher levels post-2013. Improved seed adoption followed an upward trend, with modest rises in the mid-2000s due to increased awareness and support, spiking around 2013-2014, followed by fluctuations and stabilization by 2021-2022. Irrigation levels were stable initially, then gradually declined from the late 1990s, briefly recovered between 2007 and 2010, but dropped sharply post-2015. A slight recovery occurred after 2020, though overall levels remained lower than pre-2015, reflecting long-term challenges for sustainable agricultural productivity.

Descriptive Statistics

Table (1) summarizes the statistics of 32 variables used in the study. Skewness indicates that LAGR, LMAT, LMIT, LFERT, and LIRRIG are negatively skewed (< 0), while LPREC, LCO2, and LIMPS are positively skewed (> 0). Kurtosis values reveal that LAGR, LMAT, LPREC, LCO2, and LFERT are platykurtic (less than 3), whereas LMIT, LIMPS, and LIRRIG are leptokurtic (greater than 3). Normality testing using the Jarque-Bera test rejects the null hypothesis of normal distribution for LIMPS and LIRRIG ($p < 0.05$), but not for the other variables.

Table 1: Descriptive Analysis

Variables	LAGR	LMAT	LMIT	LPREC	LCO2	LIMPS	LFERT	LIRRIG
Mean	6.023	2.977	2.262	7.424	8.340	8.438	11.065	9.995
Median	6.012	2.979	2.265	7.424	8.072	8.209	11.113	10.181
Maximum	6.271	3.028	2.356	7.651	9.74	10.452	12.900	10.799
Minimum	5.668	2.918	2.138	7.211	7.075	7.492	8.057	8.008
S.D.	0.185	0.029	0.043	0.099	0.800	0.888	1.389	0.684
Skewness	-0.4177	-0.024	-0.671	0.0299	0.395	1.278	-0.418	-1.449
Kurtosis	1.945	2.356	3.874	2.840	2.055	3.535	2.388	4.738
Jarque-Berra	2.411	0.555	3.424	0.038	2.026	9.096	1.431	15.239
Probability	0.299	0.757	0.180	0.980	0.363	0.010	0.488	0.000
Sum	192.753	95.273	72.386	237.59	266.886	270.033	354.105	319.867
Sum Sq. Dev	1.067	0.026	0.0581	0.308	19.858	24.451	59.870	14.541
Observations	32	32	32	32	32	32	32	32

Empirical discussion

Stationarity tests results

It is essential to define the sequence of integration before looking into the cointegration among the variables. Furthermore, using more than one unit root test to determine the integration order of series is also very important because efficiency of the unit root differs on the basis of sample size. This paper applied Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests to check the stationarity of the variables. The results of the tests are presented in table 2 which shows LMAT, LMIT, LPREC are stationary at I(0), whereas LAGR, LCO2, LIMPS, LFERT and LIRRIG are stationary at I(1). Hence, suggesting to apply the ARDL model to explore long run and short run relationship among the selected variables.

To get the structural breaks in the data, (Zivot & Andrews, 2002) structural break trended unit root test is implemented and the results are presented in table 3 and the results also verify the standard unit root tests.

Table 2: Results of ADF, P-P, and KPSS unit root tests

Variables	Unit Root Tests		
	ADF	PP	KPSS
Levels			
LAGR	-2.0712	-2.0712	0.1455
LMAT	-3.8046*	-3.7925*	0.5331*
LMIT	-4.1721*	-4.1746*	0.1287*
LPREC	-4.2322*	-4.2322*	0.1064*
LCO2	-2.6044	-1.6450	0.1331
LIMPS	1.0268	-1.8670	0.6382
LFERT	-1.1346	-1.2241	0.1601
LIRRIG	-1.1362	-2.5634	0.3811
First Differences			
ΔLAGR	-6.0275*	-6.0870*	0.5771*
ΔLMAT	-8.7421*	-15.7798*	0.1493*
ΔLMIT	-6.8600*	-15.5867*	0.2786*
ΔLPREC	-10.1502*	-10.5021*	0.3612*
ΔLCO2	-3.9002*	-5.1881*	0.1123*
ΔLIMPS	-11.6312*	-11.6312*	0.2104*
ΔLFERT	-6.5057*	-6.4409*	0.2063*
ΔLIRRIG	-7.3245*	-5.1057*	0.3101*

*Note:- * exhibits significance at 1% level.*

Table 3: Zivot-Andrews (Z-A) structural break unit root test

Variables	**ZA Test for Level**			**ZA Test for 1st Difference**		
	T-statistic	**Time-Break**	**Outcome**	**T-statistic**	**Time-Break**	**Outcome**
LAGR	-3.434	2016	Unit Root	-6.593*	2011	Stationary

LMAT	-5.212*	2017	Stationary	-6.245*	2011	Stationary
LMIT	-4.574***	2010	Stationary	-5.205**	2014	Stationary
LPREC	-5.846*	2004	Stationary	-10.831*	1997	Stationary
LCO2	-3.965	2016	Unit Root	-5.561*	2008	Stationary
LIMPS	-3.008	1998	Unit Root	-7.007*	2013	Stationary
LFERT	-3.848	2009	Unit Root	-10.344*	2009	Stationary
LIRRIG	-3.504	2008	Unit Root	-8.063*	2005	Stationary

*Note:- *, **, *** exhibits stationarity at 1%, 5% and 10% significance level respectively.*

ARDL Bounds Test

Results of the cointegration test with ARDL bound is presented in the table 4, the results show that the estimated F-statistics value (5.838000) is larger than 10%, 5%, 2.5%, and 1% of the critical upper limit in the order zero and one respectively, rejecting the null hypothesis by demonstrating that the variables have a long-run association.

Table 4: ARDL cointegrating results

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	5.838000*	10%	2.38	3.45
k	7	5%	2.69	3.83
		2.5%	2.98	4.16
		1%	3.31	4.63

*Note:- * exhibits significance at 1% level*

Long run and Short run estimates

Overall results of the ARDL model for long run and short run estimates is presented in the table 5 and table 6 respectively. It provides insights into the long-run and short-run relationships between agricultural productivity, various climatic variables and various agricultural input factors.

The coefficient for LMAT (2.775077) is positive and statistically significant at the 1% level, indicating that higher annual average maximum temperatures are associated with increased agricultural productivity in the long run. This relationship is plausible in regions where crops benefit from warmer temperatures, assuming that other conditions such as water and soil quality are optimal. Moderate temperature increases may boost yields, especially in cooler climates. Farmers' adaptation strategies, such as adjusting planting schedules or crop varieties, could also mitigate potential negative impacts (Lobell & Field, 2007).

In contrast, coefficient for LMIT (-1.184312) is negative and significant, indicating that higher minimum temperatures harm long-run agricultural productivity by increasing respiration rates that reduce net carbon assimilation or shortening the growing season . This aligns with studies showing that excessive increases in minimum temperatures negatively impact crops, especially those needing cooler nights (Peng et al., 2004).

For other climatic factors such as the coefficient for LCO2 and LPREC the coefficient is (0.074655) and (0.139982) respectively both representing statistically insignificant, indicating CO_2 emissions have no significant long-run impact on agricultural productivity in this model. Although CO_2 can enhance photosynthesis, its effect may be offset by other factors like nutrient availability. Studies show mixed results on CO_2's impact, depending on crop type and environmental conditions (Long et al., 2006) and the reason for precipitation may be due to the complexity of precipitation's impact, which depends on timing, intensity, and soil water retention. Studies indicate that the relationship between precipitation and crop yields is often nonlinear and region-specific (Mahadevan et al., 2024).

The short-run coefficients for climatic variables is presented in table 5, which are all statistically significant, indicating that changes in these variables have immediate impacts on agricultural productivity. A short-run increase in maximum temperature Δ(LMAT) positively affects productivity, while an increase in minimum temperature Δ(LMIT) and precipitation Δ(LPREC) negatively affects it, consistent with their long-run effects.

Discussing on the long run coefficient of agricultural input factors as the measures of adaptation, the coefficient for LFERT (-0.040978) is negative and significant, indicating that increased use of chemical fertilizers reduces long-term agricultural productivity. This may be due to the negative effects of excessive or improper fertilizer use, which can degrade soil health. Literature supports this, showing over-reliance on fertilizers can cause soil acidification, nutrient imbalances, and pollution, harming productivity as per the study of (Shrestha et al., 2021).

The coefficient for LIRRIG (0.028942) is positive and marginally significant, suggesting that improved irrigation enhances long-term agricultural productivity. Adequate irrigation is crucial for stable crop yields, especially under irregular rainfall patterns. This aligns with the view of (Misra, 2014) that reliable water supply mitigates climate change risks.

The coefficient for LIMPS (0.064088) is positive but not statistically significant, indicating that improved seeds may enhance productivity, though the effect is weaker than irrigation. The impact of seed use depends on factors like soil fertility and water availability. Study like (Choudhary et al., 2020) suggest improved seeds boost productivity when combined with other agricultural best practices, but their effectiveness can be limited by environmental conditions.

For the agricultural inputs in the short run, The coefficient for Δ(LIMPS) (0.024460) is positive and significant, showing that improved seeds have a positive short-run impact on agricultural productivity. This suggests immediate yield gains due to enhanced resistance to pests, diseases, and climate stresses.

Improved seeds contribute to better short-term agricultural outcomes. The short-run coefficient for Δ(LFERT) was not reported, but given the long-run negative relationship, its short-run effects may be insignificant or context-dependent. The short-run impact of irrigation, though not directly provided, likely aligns with the long-run positive effect, helping stabilize productivity amid climatic variability.

The Error Correction Term CointEq(-1) is negative and statistically significant (-0.643144, $p = 0.0000$), indicating that deviations from the long-run equilibrium are corrected by approximately 64.31% in the following period. This significant and negative coefficient confirms the existence of a long-run relationship, with the system adjusting back to equilibrium fairly quickly.

Table 5: Long run coefficient using the ARDL approach (1,1,1,0,1,0,1,1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LMAT	2.775077*	0.733112	3.785339	0.0015
LMIT	-1.184312*	0.361488	-3.276217	0.0045
LCO2	0.074655	0.063284	1.179681	0.2544
LPREC	0.139982	0.116373	1.202877	0.2455
LFERT	-0.040978**	0.016029	-2.556582	0.0204
LIMPS	0.064088	0.038178	1.678685	0.1115
LIRRIG	0.028942***	0.014097	2.053154	0.0558
R-squared	0.989865	Mean dependent var		6.033828
Adjusted R-squared	0.982115	S.D. dependent var		0.179135
S.E. of regression	0.023957	Akaike info criterion		-4.322694
Sum squared resid	0.009757	Schwarz criterion		-3.675087
Log likelihood	81.00176	Hannan-Quinn criteria		-4.111590
F-statistic	127.7223	Durbin-Watson stat		2.338456
Prob(F-statistic)	0.000000			

Table 6:- Error correction representation of ARDL model (1,1,1,0,1,0,1,1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.098457*	0.138585	-7.926215	0.0000
@TREND	0.005089*	0.000790	6.445484	0.0000
Δ(LMAT)	0.622630*	0.142723	4.362513	0.0004
Δ(LMIT)	-0.193092*	0.078552	-2.458134	0.0250
Δ(LPREC)	-0.097296*	0.031181	-3.120354	0.0062
Δ(LIMPS)	0.024460*	0.006299	3.883432	0.0012
CointEq(-1)*	-0.643144*	0.079205	-8.120041	0.0000
R-squared	0.755558	Mean dependent var		0.018283
Adjusted R-squared	0.694447	S.D. dependent var		0.036475
S.E. of regression	0.020162	Akaike info criterion		-4.774307
Sum squared resid	0.009757	Schwarz criterion		-4.450503
Log likelihood	81.00176	Hannan-Quinn criteria		-4.668755
F-statistic	12.36378	Durbin-Watson stat		2.338456
Prob(F-statistic)	0.000002			

*Note:- in table 5 and table 6 *, **, *** exhibits stationarity at 1%, 5% and 10% significance level respectively.*

Diagnostic Tests

The estimated ARDL model also requires diagnostic testing for robustness. Table 7 presents the diagnostic tests, where the value of F-statistic in BG test is (1.363044) with a Prob F(1,16) of (0.2601). This probability value is greater than the usual significance levels (i.e, 0.05 or 0.01), implying that we fail to reject the null hypothesis of no serial correlation in the residuals. Again, the Obs *R-squared (2.433580), with a Prob. Chi-Square (1) of (0.1188). Again, since this p-value is higher than common significance levels, confirming that there is no evidence of serial correlation in the residuals.

The results of BPG test for heteroskedasticity indicates that there is no evidence of heteroskedasticity in the model. It is because the value of F-statistic (1.007599) with p-value (0.4850) is greater than common significance levels like 0.05 which means we fail to reject the null hypothesis of homoscedasticity. Value of Obs *R-squared is (13.49099) with Prob Chi-Square (13) is (0.4106) also indicating that we fail to reject the null hypothesis, further supporting the conclusion of no heteroskedasticity and at last scaled explained SS of (3.664315) has a Prob Chi-Square(13) of (0.9943) indicating no evidence of heteroskedasticity and confirming that the ARDL model is properly fitted and the residuals are normally distributed ($p > 0.05$) as shown in figure 2

Table 8 presents multicollinearity tests. The Variance Inflation Factor (VIF) values presented indicate the level of multicollinearity between the independent variables in your model. LMAT (1.81), LMIT (1.17), LPREC (1.15), LFERT (1.98), and LIRRIG (1.54) these VIF values are all below 5, which is generally considered a safe threshold. This suggests that there is low multicollinearity for these variables. LIMPS (2.99), while this is higher than the others, it's still below the threshold of 5, indicating manageable multicollinearity. LCO2 (4.57), although this is the highest VIF value, it is still below 5, so it doesn't raise major concerns but indicates higher multicollinearity compared to the other variables.

An overall mean VIF of (2.17) is considered acceptable and suggests that multicollinearity is not a severe issue in our model. In summary, none of the variables have problematic multicollinearity, as all VIF values are below the common threshold of 5. Therefore, multicollinearity does not seem to pose a major issue in our model.

Additionally, figure 2 displays the results of both the CUSUM and CUSUM of squares tests, indicating that the estimated long-run and short-run parameters of the model remain stable throughout the study period.

Table 7:- Results of the diagnostic tests

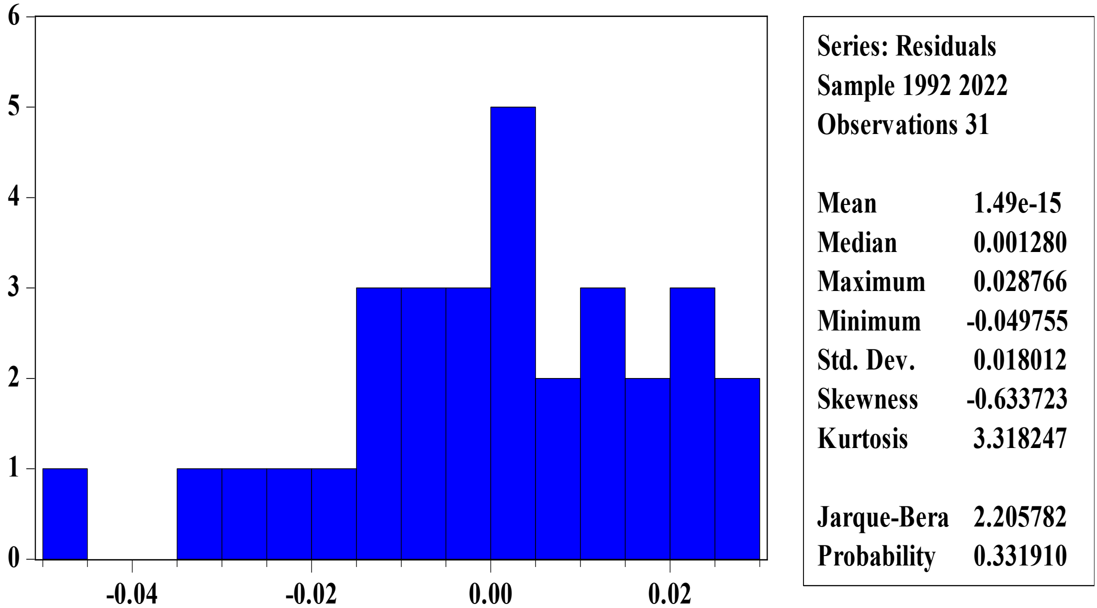
Breusch-Godfrey Serial Correlation LM Test:

F-statistic	1.363044	Prob F(1,16)	0.2601
Obs *R-squared	2.433580	Prob. Chi-Square (1)	0.1188

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	1.007599	Prob F(13,17)	0.4850
Obs *R-squared	13.49099	Prob. Chi-Square(13)	0.4106
Scaled explained SS	3.664315	Prob. Chi-Square(13)	0.9943

Figure 2:- Normality of the residuals

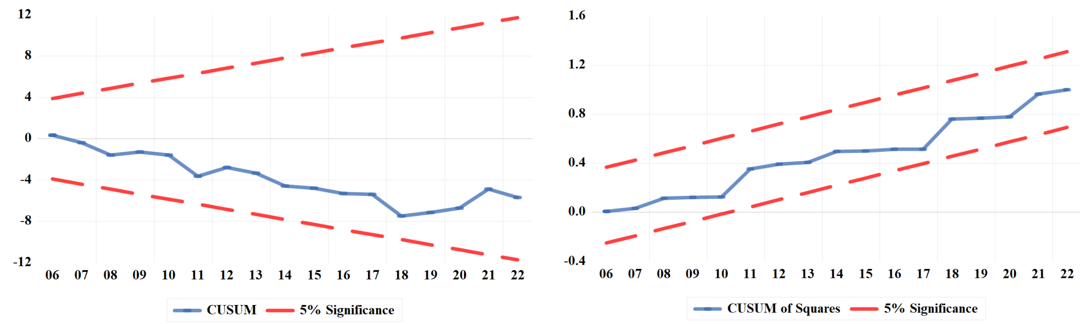


The normality test of the residuals in the above figure 2, suggests that they are approximately normally distributed. The histogram shows a symmetric distribution centered around zero, indicating no significant deviations from normality. Key statistics further support this observation. The skewness value of -0.633723 indicates a slight negative skew, while the kurtosis value of 3.318247 is close to 3, suggesting the residuals have tails similar to a normal distribution. The Jarque-Bera statistic of 2.205782, with a p-value of 0.331910, confirms that the null hypothesis of normality cannot be rejected, as the p-value is greater than the 0.05 significance level. Overall, the residuals meet the normality assumption required for the model.

Table 8:- Variance Inflation Factor (VIF) test for multicollinearity

Variable	VIF	1/VIF
LMAT	1.81	0.5510
LMIT	1.17	0.8538
LCO2	4.57	0.2188
LPREC	1.15	0.8727
LFERT	1.98	0.5042
LIMPS	2.99	0.3343
LIRRIG	1.54	0.6488
Mean VIF	2.17	

Figure 3:-Plots of Cumulative Sum (CUSUM) of recursive residual and Cumulative Sum (CUSUM) of Squares of residuals



Toda-Yamamoto Granger Causality Test

The results of TY Granger Causality Test also reveals that LMAT, LMIT, LIMPS, LFERT, have unidirectional causality towards LAGR implying that past values of these variables provide useful information to predict LAGR, and this results are also consistent with ARDL estimation results presented in table 5 and table 6 .Variables LPREC and LIRRIG are found to have bidirectional causality with LAGR.

Variables	LAGR	LMAT	LMIT	LPREC	LCO2	LIMPS	LFERT	LIRRIG
LAGR	-	8.397*	2.576**	13.836*	8.753	11.674*	23.72*	8.272*
LMAT	3.069	-	4.579***	1.368	8.284*	1.327	7.780**	3.026
LMIT	0.419	2.770	-	2.820	0.566	0.307	0.093	2.405
LPREC	31.49*	1.126	8.511**	-	22.36*	3.713	5.879**	18.079*
LCO2	1.805	3.412	3.031	2.733	-	6.976	0.806	6.349**
LIMPS	1.8205	4.261	1.102	3.248	2.297	-	1.774	2.110
LFERT	12.11*	4.313	21.81*	7.857**	16.647*	16.703*	-	4.95***
LIRRIG	0.5393	8.270*	8.171*	2.863	12.689*	7.541**	0.431	-

Table 9:- Toda-Yamamoto Granger Causality Test

*Note:- *, **, *** exhibits stationarity at 1%, 5% and 10% significance level respectively.*

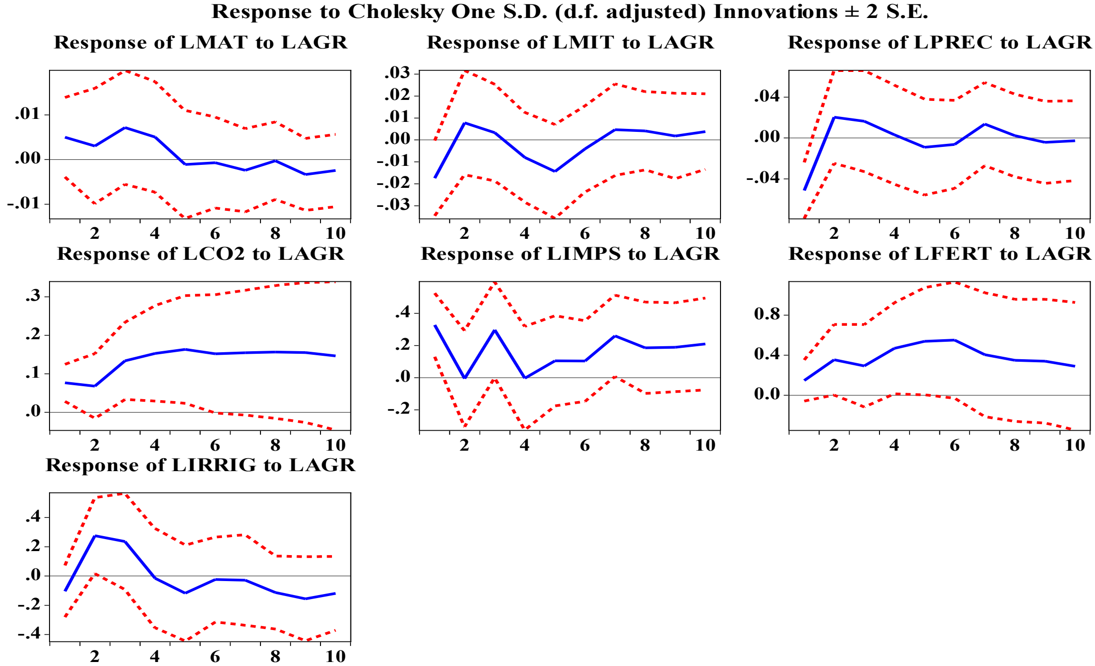
Generalized Impulse Response Function

The study uses generalized impulse response analysis to examine how shocks in one variable affect another and to understand the short-run impact of innovations across all variables in the system of agricultural productivity. This approach provides insights into the dynamic responses between variables (Pesaran & Shin, 1995). The generalized impulse responses of climatic variables and other selected variables to one standard deviation innovations in agriculture productivity are visualized in figure 4.

A positive shock to maximum temperature initially boosts agricultural productivity, peaking shortly after and then gradually declining. In the long run, the positive effect diminishes but remains slightly above zero, indicating a sustained yet reduced benefit. This may be due to enhanced photosynthesis or longer growing seasons. Minimum temperature shocks also initially increase productivity, but the effect turns negative over time, possibly due to increased plant respiration or pests. Precipitation shocks initially enhance productivity, but excessive rainfall leads to long-term negative impacts such as waterlogging and soil erosion. For CO2 emissions, positive shocks consistently improve productivity due to the CO2 fertilization effect. Improved seeds show immediate and significant gains, stabilizing over time as the benefits of resilient seed varieties become consistent.

Chemical fertilizers provide a substantial short-term boost, though the effect slightly declines, emphasizing the need for balanced use. Irrigation increases productivity initially, but over time, inefficient management can lead to negative effects like soil salinity, stressing the importance of sustainable irrigation practices.

Figure 4:- Generalized impulse responses



Conclusion and Recommendation

In this study, the analysis revealed a complex relationship between these climatic variables and agricultural output in Nepal. The annual average maximum temperature positively affects agricultural productivity in the long run, indicating that an increase in temperature can boost crop yields in regions where crops are sensitive to higher temperatures.

This positive effect is likely due to farmers' adaptation strategies, such as adjusting planting schedules and using heat-tolerant crop varieties. On the other hand, the annual average minimum temperature negatively impacts productivity, as higher night-time temperatures can disrupt crop growth by shortening the growing season and increasing respiration rates, which reduces net carbon assimilation.

Interestingly, the study found that CO2 emissions and precipitation did not have statistically significant long-term effects on agricultural productivity. While CO2 fertilization can enhance photosynthesis, its impact in this context may be offset by other limiting factors such as nutrient availability. Similarly, precipitation's effect on productivity is complex and highly dependent on timing, intensity, and soil water retention capabilities.

In the short run, however, changes in maximum temperature, minimum temperature, and precipitation were all found to have significant and immediate effects on agricultural productivity, indicating the system's quick adjustment to climatic variations. These findings underscore the importance of adaptive strategies in agriculture to mitigate the adverse effects of climate change, emphasizing the need for flexible, context-specific approaches that address both the immediate and long-term challenges posed by shifting climatic patterns.

In the long run, the analysis of agricultural input factors reveals a nuanced impact on productivity. The use of chemical fertilizers, while often associated with increased crop yields, shows a negative and statistically significant effect on agricultural productivity over time. This suggests that excessive or improper use of chemical fertilizers may lead to soil degradation, ultimately reducing long-term productivity. Such findings highlight the potential adverse effects of relying heavily on chemical inputs without sustainable practices.

Conversely, irrigation practices exhibit a positive, albeit marginally significant, impact on agricultural productivity in the long run. This underscores the importance of reliable water supply in maintaining and enhancing crop yields, especially in regions facing variable climatic conditions. Effective irrigation systems are crucial for ensuring that crops receive adequate water, particularly in the face of increasing temperature and unpredictable rainfall patterns.

The adoption of improved seeds, while expected to boost productivity, does not show a statistically significant effect in the long run. This indicates that the benefits of improved seed varieties might be influenced by other factors such as soil fertility, climate conditions, and the integration of other agricultural practices. However, in the short run, the coefficient for improved seeds is positive and significant, demonstrating that the adoption of these varieties has an immediate and beneficial impact on agricultural productivity. This finding suggests that while improved seeds can enhance yields quickly, their long-term success depends on a holistic approach that considers the broader agricultural environment.

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