



Assessing the impacts of climatic and technological factors on rice production: Empirical evidence from Nepal

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ABSTRACT

Considering the significant impact of climate change on major staple food crops in Nepal, this study aims to estimate the influence of climatic factors (i.e., CO₂ emissions, average temperature, and average precipitation) and technological factors (i.e., fertiliser consumption and improved seeds) on rice production in Nepal from 1990 to 2016 using the autoregressive distributed lag (ARDL) approach. While controlling for cultivated rice areas, agricultural credit variables are likely other essential rice production factors. This study reveals a long-run cointegration connection among the variables. The ARDL results indicate that CO₂ emissions decreased rice production by 0.13%, while average temperature and average precipitation improved rice production by 0.72% and 0.01%, respectively, in the long run. Further results show that cultivated rice area, fertiliser consumption, and agricultural credit enhanced rice production by 2.26%, 0.05%, and 0.02%, respectively, in the long run. Unidirectional causality among cultivated areas, fertilisers, seeds, temperature, CO₂ emissions, and rice production was confirmed. Additionally, impulse response and variance decomposition verified the substantial impacts of climate and technological factors on rice production and variations. This study empirically confirmed that the use of agricultural technology (i.e. fertiliser consumption) significantly enhanced rice production; therefore, this study suggests that the Nepalese government should expand subsidised fertilisers so as to increase rice production and improve the income of farmers. In addition, agricultural credit plays a vital role in enhancing rice production in Nepal; to cope with climate change, the study also suggests that there is a need to launch carbon/weather financing schemes through financial intuitions in the country.

1. Introduction

It is predicted that, owing to the high concentration level of emissions in the atmosphere and other greenhouse gas (GHG) emissions, temperatures will increase and rainfall patterns will change [1]. The agricultural sector is more sensitive and vulnerable to climate change. Many cereal crops (i.e. rice, wheat, and maize) are the most grown and consumed worldwide. However, the yield of cereal crops is significantly affected by climate change. Variations in climate change affects food security and rural household livelihoods severely, particularly in developing nations [2]. In South Asia (SA) and Sub-Saharan Africa (SSA), Kumar and Singh [3] estimated that food crops grown will decline by 4%–10% and 12%, respectively, in the 2070–99 period with

2.3°C–4.5 °C temperature increase. Furthermore, they anticipated that food crop production in South East Asia would improve with increasing temperature. Many empirical studies have assessed the impact of climatic and non-climatic factors on rice production in major rice-producing countries of the world [4–9].

In a recent study, Chandio et al. [5] showed that CO₂ emissions have a positive influence on rice production in Pakistan. Similarly, Casemir and Diaw [10] found that CO₂ emissions affect Benin's agricultural production negatively. In Bangladesh, a study conducted by Sarker et al. [11] revealed that the average minimum temperature is more favourable for rice production, whereas the average maximum temperature affects rice production adversely. Sarker et al. [12] reported that increase in temperature, precipitation, solar radiation, floods, and

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droughts affect agricultural productivity negatively. However, regardless of advanced knowledge, climate change remains a key hurdle in boosting agricultural productivity and livelihood. In SA, global warming is already reducing major food crop yields and unsettling food systems.

Nepal is among the world's least developed countries and is highly vulnerable to the effects of climate change. Nepal is an agro-based country in SA. The agricultural sector plays a leading role in the economy, contributing 26.98% to the GDP and employing two-third of its labour force [13]. In Nepal, about 80% of households rely on agriculture to meet their daily needs. The agricultural sector provides a leading source of livelihood for Nepalese people, and it has played a vital role in poverty reduction and employment generation [14]. Additionally, owing to the rising population growth rate, food demand has increased in the country. Cereal crops like rice, which are produced and consumed by 90% of the people around the world, are highly affected by fluctuations in climate change. As highlighted by IPCC [15], an increase of 1 °C in temperature will lead to water scarcity and land degradation, affect food security, and globally reduce rice yield by 3.2%. At present, Nepal's agricultural sector faces several challenges: climatic variations, changes in rainfall patterns, increase in temperatures, rise in GHG emissions, scarcity of water, and shortage of basic inputs for agricultural production.

Overall, agricultural production is heavily affected by climate change. Variations in temperature and precipitation negatively affect land and water resources, which affects agricultural growth [16]. In Nepal, approximately 76% of rural households grow rice crops, and it is the most preferred staple food for Nepalese people [17]. Presently, rice production is low and uncertain [18]. Almost two-third of rice is cropped with rainfall, and it is susceptible to climate change [19]. Nepal faces a dearth of sufficient irrigation facilities, and irrigation infrastructure covers only 55.7% of the total arable agricultural land [19]. Therefore, productivity and food security are primarily influenced by the degree of rainfall [20]. However, monthly rainfall has declined by an average of 3.2 mm per decade, while temperature has increased by 0.06 °C yearly. Climate change influences food production, consumption, and distribution negatively. It is further expected that Nepal's food production will reduce by 3.5% and 12.1% in the 2050s and 2080s, respectively [21]. Higher vulnerability to climate change has brought many negative consequences; for instance, natural disaster had damaged 0.144 million hectares of cultivated land in 2017/18.

This study investigates the influence of climate change and technical progress in rice production in Nepal from 1990 to 2016. Most studies have analysed only rice market integration [17], adoption of improved technologies [22–24], climate change, natural disasters [25], and social capital–food security nexus [26] in the context of Nepal. However, this study explores both short- and long-run effects of climatic factors (i.e., CO₂ emissions, average precipitation, and average temperature) on rice production using the autoregressive distributed lag (ARDL) model. We explore not only the effects of climatic factors but also the effects of essential input factors (i.e., cultivated area, fertilisers consumption, improved seed, and agricultural credit) on rice production. The remainder of this paper is organised as follows. Section 2 discusses the rice production outlook in Nepal, and Section 3 reports an extensive review of related studies. Section 4 discusses the methodology and data, and Section 5 provides the empirical findings. Finally, section six concludes the study.

2. Nepal and its rice production

The agricultural sector mainly contributes to reducing poverty and improving the living standards of the vast population of low-income countries like Nepal. Agriculture is the primary occupation of 80% of rural households in Nepal, which rely directly on agriculture for their livelihoods. Approximately 20% of the total area is used for farming-related activities. Rice is one of the most consumed staple foods globally, accounting for over half of the world's population. Asia alone

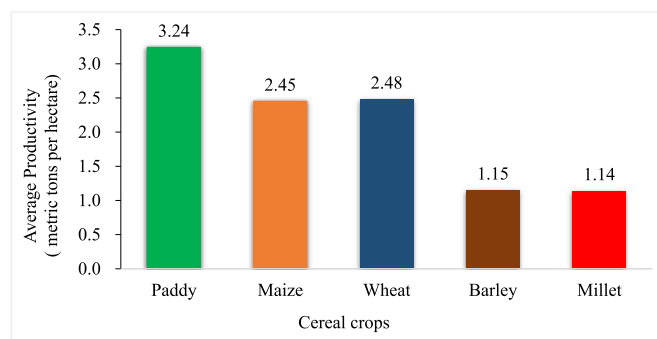


Fig. 1. Average productivity of cereal crops in Nepal.

Data Source: Economic Survey of Nepal, (2018/19)

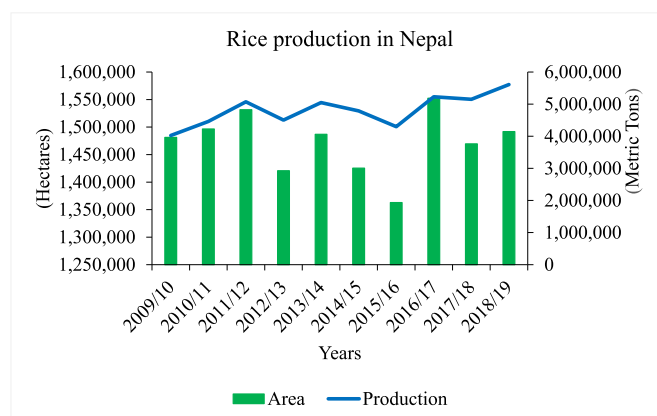


Fig. 2. Rice production in Nepal from 2009/10 to 2018/19.

Data Source: Economic Survey of Nepal (2018/19)

accounts for 90% of the global rice production [27]. In cereal crops, rice is a staple food for Nepalese people. Rice alone contributes 20.8% of the agricultural GDP of Nepal [19]. Rice has been contributing significantly to the food security conditions of rural households in Nepal. The crop is grown widely in agro-ecological regions covering Terai to mountain basins and hills. Rice production accounts for over 80% of the total cultivated land, with an area of 1.49 million hectares (Mhs) [19]. In Nepal, rice productivity was enhanced by 8.9% in 2018/19 from 7.3% in 2017/18, taking the lead among other cereal crops. Fig. 1 illustrates the average productivity of the main food crops in Nepal in 2018/19. The productivity of cereal crops, including rice, is not sufficient to meet the domestic demand. Moreover, rice production in Nepal is anticipated to fluctuate as a result of climate change.

In Nepal, 1.48 Mhs was the estimated cultivation area for rice production of 4.02 Mts in 2009/10. During 2015/16, the cultivated area and rice production decreased severely owing to dry weather and low input adoption. Whereas in 2018/19, out of the total agricultural cultivated land area of 3.091 Mhs, an area of approximately 1.49 Mhs was occupied by rice production, and 5.61 Mts of rice was produced in the country (See Fig. 2). As per the report of MoAD [19], out of the total rice production of 5610 Mts in 2018/19, production in Province No.2 was high, approximately 27%, while it was 22% and 21% in Province No.5 and No.1, respectively. The Karnali province had the lowest share (2.6%) in the same period.

To meet domestic demand, Province No.s 1 and 2 produced large quantities of rice in the country. More than 80 varieties of rice, including two hybrids, were released by Nepal until 2020. Several rice varieties (i.e., Mansuli, Jeera-Masino, Chaite-2, and Mahsuri) are widely grown in Nepal, as the soil is fertile and climatic conditions are favourable. Although rice productivity has increased, it is still insufficient to meet

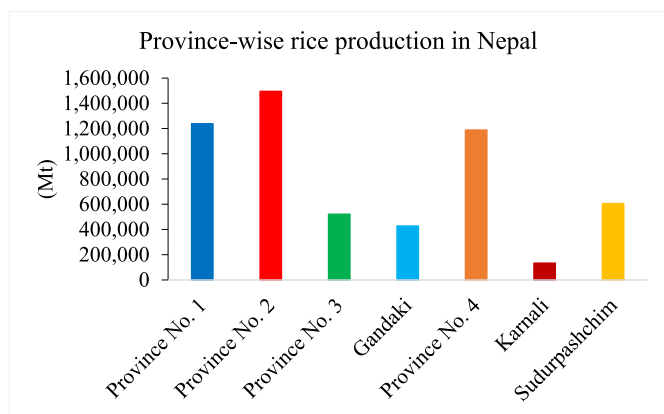


Fig. 3. Province-wise rice production in Nepal in 2018/19).
 Data Source: Economic Survey of Nepal (2018/19)

domestic demand. Over 70% of the total rice is produced and consumed as a staple food in the country [28]. Province No.2 has the largest rice-producing area in Nepal at 26.9%. In 2018/19, Province No.s 1, 2, and 5 produced high quality of rice, about 1.24, 1.5, and 1.19 million tons, respectively. Fig. 3 reports the province-wise rice production in metric tons, with Province 2 recording the highest and the Karnali province recording the lowest production in 2018/19. Along with the increase in rice production, imports in Nepal have also been surging, implying consumption escalation. Nepal exports up to \$45 million worth of rice to India every year. In 2015, Nepal imported 53,100 tons of rice worth \$210 million from India.

The rise in imports is due to insufficient growth in productivity, increase in population, and increased domestic demand. Many empirical studies have examined the effects of climate change, cultivated area, and rural labour force on cereal production in developing countries [29–32]. However, these studies omitted other necessary direct inputs such as improved quality of seeds and fertiliser consumption, and indirect inputs such as formal credit. In the current study, we attempt to answer the following questions: First, what is the effect of climate change (via CO₂e, annual average temperature, and annual average rainfall) on rice production in the SHT and LT? Second, what is the impact of direct and indirect inputs on rice production in the SHT and LT? This empirical study contributes significantly to the existing literature as it is the first, to the best of our knowledge, to explore the SHT and LT impacts of climate change and technological factors on rice production in Nepal

using the ARDL framework. The direction of association among variables were fertiliser c fertiliser consumption verified by the Vector Autoregressive Model (VAR) Granger causality test. Fig. 4 presents the conceptual framework showing climate change factors and other direct and indirect inputs (e.g., cultivated area, fertiliser consumption, improved seeds, and agricultural credit) that may affect Nepal’s rice production.

3. Literature review

Currently, climate change has become a severe global issue, and a greater percentage of the population has to deal with its consequences in different ways. The agricultural sector is expected to be affected adversely owing to rising variability of temperatures [33], frequency and intensity of extreme weather events [34], and low level of adaptation [35–37]. South Asia is among regions that are most vulnerable to the effect of climate change globally [38] with higher population growth, natural resource degradation, poverty, and food insecurity [39, 40]. Climate change severely affects the agricultural sector of developing countries, and is a prime concern for policymakers, researchers, and other organisations. Various researchers have undertaken numerous studies worldwide to estimate the influence of climate change on agriculture [32,41–44].

A few empirical studies have revealed that climate change in developing countries has a more significant effect on agriculture compared to developed countries [45–48]. However, the degree of influence depends on the extent of climate change and other variables [28]. Changes in temperatures could potentially affect crops directly by affecting their physiology; crop production will be indirectly affected because of more diseases, pests, and changes in the water regime [49, 50]. Climate and weather are the primary determinants of agricultural production in various regions worldwide [51]. Guiteras [52] studied the impact of random year-to-year changes in weather on Indian agricultural productivity by utilising 40-year panel data at the district level covering 200 districts. He found that anticipated changes in climate over the 2010–2039 period decreased major crop yields by 4.5%–9%. In the long run (2070–2099) climate change impact will be dramatic, decreasing yields by 25% or more due to lack of long-run adaptations. In Africa (AF) and South Asia (SA), a study conducted by Knox et al. [53] anticipated a 15%–30% deterioration in cereal productivity and 0.75 tons/ha decrease in rice when the temperature increases 2–4 °C. The investigation further estimated that average yield changes of 17% (wheat), 5% (maize), 10% (millet), –15% (sorghum) across Africa, and

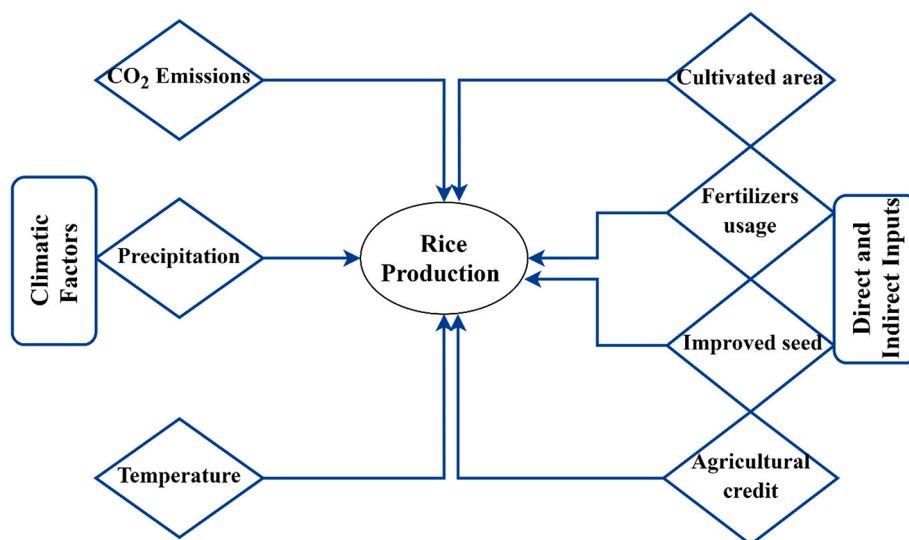


Fig. 4. Research framework of the study.

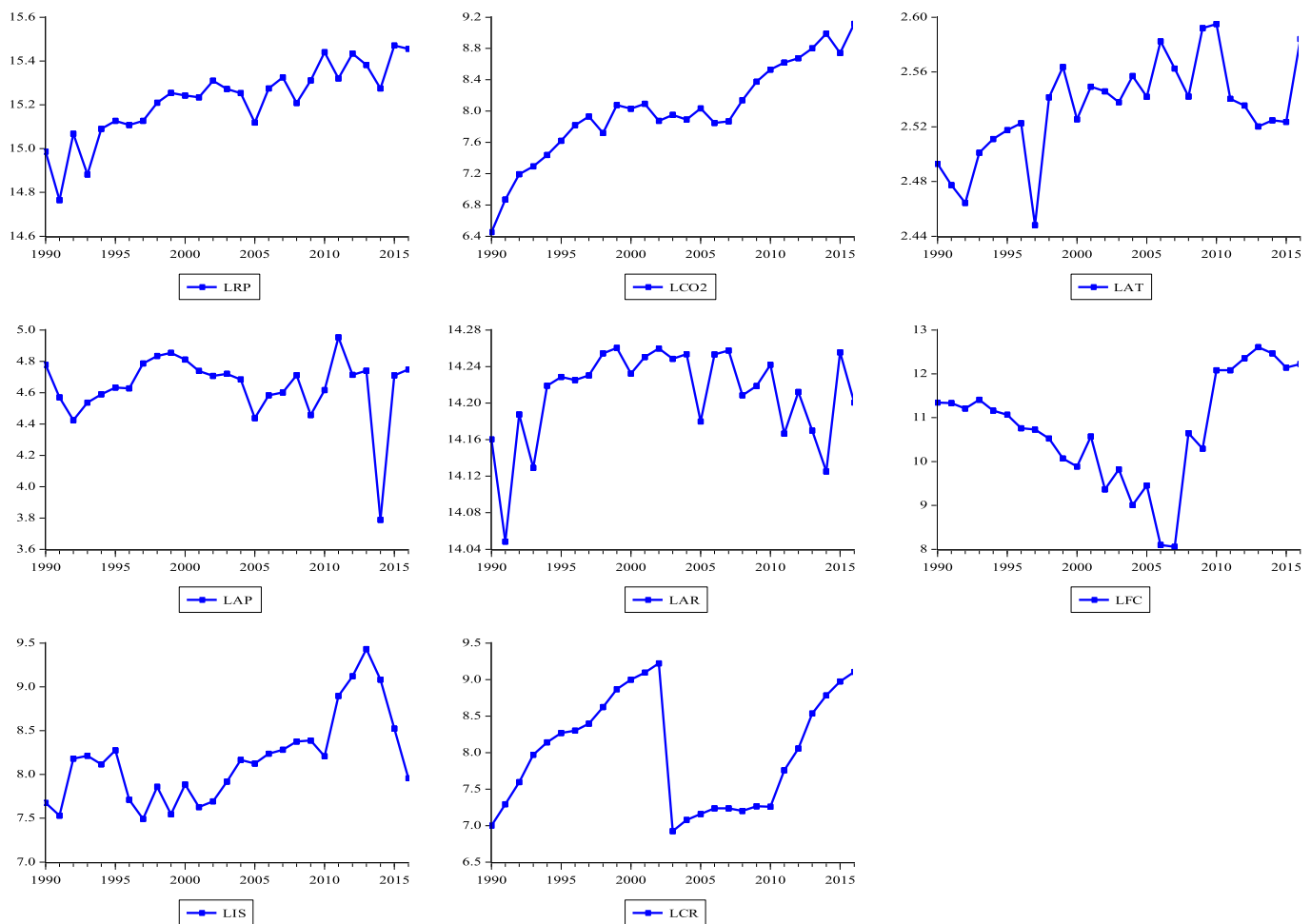


Fig. 5. Trend of variables used in the study.

–16% (maize) and –11% (sorghum) across SA. Nelson et al. [54] showed that to cope with climate change, the cost of adaptation will increase by 1.6% in wheat, 1.2% in sorghum, 0.9% in rice, 0.6% in maize, and 1.6% in millets per year owing to several agronomic methods and crop enhancements.

There is also increasing evidence among studies done that changes in precipitation levels and temperatures can adversely affect cereal yields and growth in various countries [32,55–57]. Both field and lab experiments conducted by Nagarajan et al. [58], utilising three Basmati and two non-Basmati varieties, studied the effects of diurnal temperatures and radiation. The investigation results reveal that night temperature has a significant negative influence on grain yield and quantity beyond 22 °C, while radiation positively affects the yield and quantity of grain in India. Zhou and Turvey [59] explored the effects of climate change on cereal production and concluded that the effects vary in various crop production and regions. Moreover, they found that provinces in central, northern, and western China are less vulnerable to climate change because of adaptation, but eastern provinces are very sensitive to climate change. Ali et al. [60] analysed the effect of rainfall changes and temperatures on major cereal crop production (e.g. wheat, rice, and maize). The investigation used historical time-series data from 1989 to 2015. The results revealed that maximum temperature affected wheat production negatively, whereas minimum temperature contributed positively. The study also showed that precipitation has an adverse impact on the production of wheat, rice, and maize in Pakistan.

Karn [61] investigated the interconnection between climatic factors and rice production in Nepal. The investigation used panel data from 1990 to 2015. Furthermore, this study projected and explored the

influence of climatic changes on rice production in the future. During the ripening process, the changes in maximum temperature led to increased rice yield at the threshold level of 29.9 °C. The yield of rice decreased when the maximum temperature reached this threshold level. Moreover, it was noted that the current average maximum temperature was 30.8 °C for the decade from 1999 to 2008. Therefore, rice yield is expected to be affected negatively by the increase in daily maximum temperature. Precipitation contributed to rice yield negatively during the nursery stage. Similarly, it is expected that higher morning humidity has a deleterious effect on rice growth, whereas afternoon humidity promotes growth. Additionally, the future prediction results suggest that rice yields will decrease by 4.2% compared to the current levels by 2100. The study further forecasted an estimated decline in rice yields ranging from 1.5% by 2030 to 4.2% by 2060 and 9.8% by 2090. These outcomes are also similar to previous studies' findings [62–64], which also expected a loss of crop yields from 3% to 30% in the future. Using the stochastic frontier model and spatial filtering technique, Rayamajhee et al. [28] analysed the impact of climate change on rice production in Nepal. The study utilised panel data from NLSs from 2003 to 2010. The results showed a decline of 4183 kg per household with a 1 °C rise in average summer temperature and that variation in extreme rainfall damages productivity. The results further showed that rice farmers in the study areas with access to roads and rivers are technically highly efficient. To cope with climate change, the study suggested that access to markets and irrigation infrastructure should be improved in the country. In Pakistan's context, a recent empirical work conducted by Chandio et al. [65] explored the effects of changes in CO₂ emissions and institutional credit on agricultural production. The study used annual data

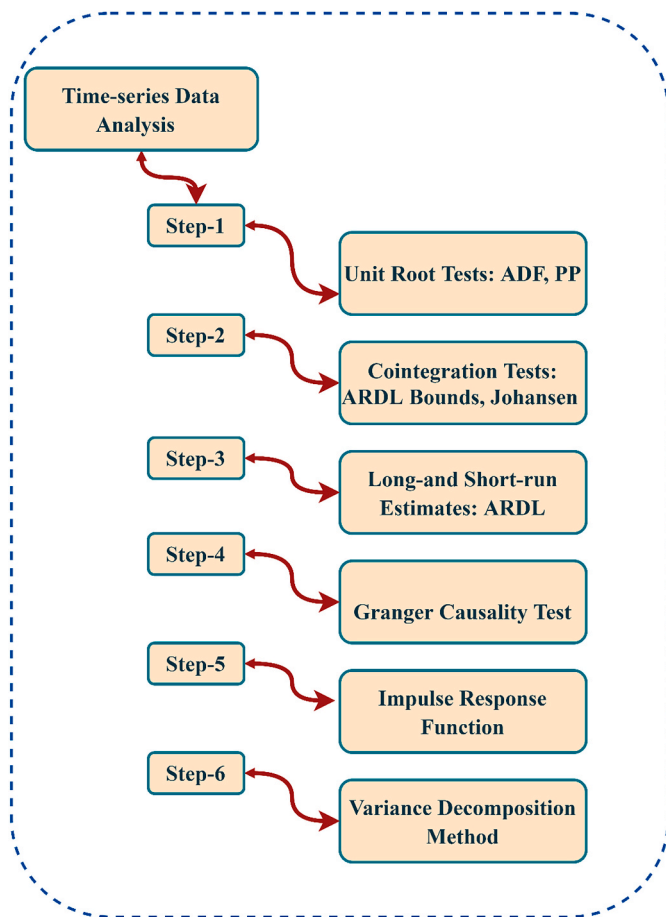


Fig. 6. Methodological flow of time-series data analysis.

from 1983 to 2016 and applied various techniques, including the ARDL, Johansen cointegration approach, and VECM to investigate the relationship between variables. The empirical outcomes revealed that in both the long-run (LR) and short-run (SR) periods, CO₂ emissions and institutional credit influenced agricultural production positively. Khan et al. [66] used panel data for 20 years (1996–2015) to assess the influence of climate conditions on maize productivity. Random and fixed-effect models were employed for the analysis. The findings revealed that the maximum temperature negatively affects maize production. Sossou et al. [30] used the OLS method to assess the yield of cereals in Burkina Faso. The investigation employed time-series data from 1991 to 2016. The findings of the investigation showed that precipitation affects cereal production positively, while temperature influences cereal production negatively. Ahmad et al. [29] specified that CO₂ emissions and climate events affected the agricultural yield severely in both the LR and SR. Additionally, the study stated that Chinese foreign direct investment significantly enhanced Pakistan’s agricultural development in both periods. Using the ARDL model and Granger causality method, Pickson et al. [67] concluded that in the LR, CO₂ emissions and temperatures significantly influence cereal production negatively, while average precipitation, cultivated area, energy utilities, and labour significantly affect cereal production in China positively. The results further revealed unidirectional flow from CO₂ emissions, energy consumption, and labour to cereal production.

4. Data and methodological path

This research aims to estimate the SR and LR impacts of climate change factors and primary agricultural inputs on Nepal’s rice production. This study is based on time-series data from 1990 to 2016. The

study extracted data from the World Bank website and various reports of Nepal’s Ministry of Agriculture and Livestock Development. The investigation used rice production (Mt) as a dependent variable, while CO₂ emissions (Kt), average precipitation (mm), average temperature (°C), cultivated area (hectares), fertiliser consumption (Mt), improved seeds (Mt), and agricultural credit (Million Rs.) were used as the independent climatic and non-climatic variables. Ahmad et al. [29], Ahsan et al. [68], and Pickson et al. [67] suggested that CO₂ emissions, average annual temperature, and average annual rainfall are suitable proxies for climate change. Warsame et al. [31] incorporated these variables into their models. Zhai et al. [69], Rehman et al. [70], and Chandio et al. [71] utilised fertiliser consumption and improved seeds as indicators of technological advancement. Fig. 5 shows the trends in the underlying variables. The methodological flow of the time-series data analysis is displayed in Fig. 6.

The current study investigates the impact of climate change factors and primary agricultural inputs on rice production in Nepal. The functional form of the model is as follows:

$$RP = f(CO_2, AT, AP, AR, FC, IS, CR) \tag{1}$$

We can rewrite Equation (1) as follow:

$$LRP = \beta_0 + \beta_1 LCO_2 + \beta_2 LAT + \beta_3 LAP + \beta_4 LAR + \beta_5 LFC + \beta_6 LIS + \beta_7 LCR + \varepsilon_t \tag{2}$$

where *LRP* is the natural log of rice production, *LCO₂* is the natural log of CO₂ emissions, *LAT* is the natural log of average temperature, *LAP* is the natural log of average precipitation, *LAR* is the natural log of rice area, *LFC* is the natural log of fertilizer consumption, *LIS* is the natural log of improved seed, and *LCR* is the natural log of agricultural credit. This investigation utilised the ARDL technique proposed by Pesaran et al. [72] to scrutinise long-term cointegration among the variables. The ARDL approach has several advantages associated with other traditional cointegrating methodologies [73,74]. First, it can measure the correct parameters if the series are integrated at I(0), I(1), or a mixed combination of both. Second, the ARDL method can estimate the LT and SHT parameters simultaneously [31,75,76].

The ARDL cointegrating equations are as follows:

$$\begin{aligned} \Delta LRP_t = & \delta_0 + \delta_1 \sum_{i=1}^p \Delta LRP_{t-i} + \delta_2 \sum_{i=1}^p \Delta LCO_{2t-i} + \delta_3 \sum_{i=1}^p \Delta LAT_{t-i} \\ & + \delta_4 \sum_{i=1}^p \Delta LAP_{t-i} + \delta_5 \sum_{i=1}^p \Delta LAR_{t-i} + \delta_6 \sum_{i=1}^p \Delta LFC_{t-i} + \delta_7 \sum_{i=1}^p \Delta LIS_{t-i} \\ & + \delta_8 \sum_{i=1}^p \Delta LCR_{t-i} + \lambda_1 LRP_{t-i} + \lambda_2 CO_{2t-i} + \lambda_3 LAT_{t-i} + \lambda_4 LAP_{t-i} \\ & + \lambda_5 LAR_{t-i} + \lambda_6 LFC_{t-i} + \lambda_7 LIS_{t-i} + \lambda_8 LCR_{t-i} + \varepsilon_t \end{aligned} \tag{3}$$

$$\begin{aligned} \Delta LCO_{2t} = & \delta_0 + \delta_1 \sum_{i=1}^p \Delta LCO_{2t-i} + \delta_2 \sum_{i=1}^p \Delta LRP_{t-i} + \delta_3 \sum_{i=1}^p \Delta LAT_{t-i} \\ & + \delta_4 \sum_{i=1}^p \Delta LAP_{t-i} + \delta_5 \sum_{i=1}^p \Delta LAR_{t-i} + \delta_6 \sum_{i=1}^p \Delta LFC_{t-i} + \delta_7 \sum_{i=1}^p \Delta LIS_{t-i} \\ & + \delta_8 \sum_{i=1}^p \Delta LCR_{t-i} + \lambda_1 LCO_{2t-i} + \lambda_2 LRP_{t-i} + \lambda_3 LAT_{t-i} + \lambda_4 LAP_{t-i} \\ & + \lambda_5 LAR_{t-i} + \lambda_6 LFC_{t-i} + \lambda_7 LIS_{t-i} + \lambda_8 LCR_{t-i} + \varepsilon_t \end{aligned} \tag{4}$$

$$\begin{aligned} \Delta LAT_t = & \delta_0 + \delta_1 \sum_{i=1}^p \Delta LAT_{t-1} + \delta_2 \sum_{i=1}^p \Delta LCO_{2t-1} + \delta_3 \sum_{i=1}^p \Delta LRP_{t-1} \\ & + \delta_4 \sum_{i=1}^p \Delta LAP_{t-1} + \delta_5 \sum_{i=1}^p \Delta LAR_{t-1} + \delta_6 \sum_{i=1}^p \Delta LFC_{t-1} + \delta_7 \sum_{i=1}^p \Delta LIS_{t-1} \\ & + \delta_8 \sum_{i=1}^p \Delta LCR_{t-1} + \lambda_1 LAT_{t-i} + \lambda_2 LCO_{2t-i} + \lambda_3 LRP_{t-i} + \lambda_4 LAP_{t-i} \\ & + \lambda_5 LAR_{t-i} + \lambda_6 LFC_{t-i} + \lambda_7 LIS_{t-i} + \lambda_8 LCR_{t-i} + \varepsilon_t \end{aligned} \tag{5}$$

$$\begin{aligned} \Delta LAP_t = & \delta_0 + \delta_1 \sum_{i=1}^p \Delta LAP_{t-1} + \delta_2 \sum_{i=1}^p \Delta LAT_{t-1} + \delta_3 \sum_{i=1}^p \Delta LCO_{2t-1} \\ & + \delta_4 \sum_{i=1}^p \Delta LRP_{t-1} + \delta_5 \sum_{i=1}^p \Delta LAR_{t-1} + \delta_6 \sum_{i=1}^p \Delta LFC_{t-1} + \delta_7 \sum_{i=1}^p \Delta LIS_{t-1} \\ & + \delta_8 \sum_{i=1}^p \Delta LCR_{t-1} + \lambda_1 LAP_{t-i} + \lambda_2 LAT_{t-i} + \lambda_3 LCO_{2t-i} + \lambda_4 LRP_{t-i} \\ & + \lambda_5 LAR_{t-i} + \lambda_6 LFC_{t-i} + \lambda_7 LIS_{t-i} + \lambda_8 LCR_{t-i} + \varepsilon_t \end{aligned} \tag{6}$$

$$\begin{aligned} \Delta LAR_t = & \delta_0 + \delta_1 \sum_{i=1}^p \Delta LAR_{t-1} + \delta_2 \sum_{i=1}^p \Delta LAP_{t-1} + \delta_3 \sum_{i=1}^p \Delta LAT_{t-1} \\ & + \delta_4 \sum_{i=1}^p \Delta LCO_{2t-1} + \delta_5 \sum_{i=1}^p \Delta LRP_{t-1} + \delta_6 \sum_{i=1}^p \Delta LFC_{t-1} + \delta_7 \sum_{i=1}^p \Delta LIS_{t-1} \\ & + \delta_8 \sum_{i=1}^p \Delta LCR_{t-1} + \lambda_1 LAR_{t-i} + \lambda_2 LAP_{t-i} + \lambda_3 LAT_{t-i} + \lambda_4 LCO_{2t-i} \\ & + \lambda_5 LRP_{t-i} + \lambda_6 LFC_{t-i} + \lambda_7 LIS_{t-i} + \lambda_8 LCR_{t-i} + \varepsilon_t \end{aligned} \tag{7}$$

$$\begin{aligned} \Delta LFC_t = & \delta_0 + \delta_1 \sum_{i=1}^p \Delta LFC_{t-1} + \delta_2 \sum_{i=1}^p \Delta LAR_{t-1} + \delta_3 \sum_{i=1}^p \Delta LAP_{t-1} \\ & + \delta_4 \sum_{i=1}^p \Delta LAT_{t-1} + \delta_5 \sum_{i=1}^p \Delta LCO_{2t-1} + \delta_6 \sum_{i=1}^p \Delta LRP_{t-1} + \delta_7 \sum_{i=1}^p \Delta LIS_{t-1} \\ & + \delta_8 \sum_{i=1}^p \Delta LCR_{t-1} + \lambda_1 LFC_{t-i} + \lambda_2 LAR_{t-i} + \lambda_3 LAP_{t-i} + \lambda_4 LAT_{t-i} \\ & + \lambda_5 LCO_{2t-i} + \lambda_6 LRP_{t-i} + \lambda_7 LIS_{t-i} + \lambda_8 LCR_{t-i} + \varepsilon_t \end{aligned} \tag{8}$$

$$\begin{aligned} \Delta LIS_t = & \delta_0 + \delta_1 \sum_{i=1}^p \Delta LIS_{t-1} + \delta_2 \sum_{i=1}^p \Delta LFC_{t-1} + \delta_3 \sum_{i=1}^p \Delta LAR_{t-1} \\ & + \delta_4 \sum_{i=1}^p \Delta LAP_{t-1} + \delta_5 \sum_{i=1}^p \Delta LAT_{t-1} + \delta_6 \sum_{i=1}^p \Delta LCO_{2t-1} + \delta_7 \sum_{i=1}^p \Delta LRP_{t-1} \\ & + \delta_8 \sum_{i=1}^p \Delta LCR_{t-1} + \lambda_1 LIS_{t-i} + \lambda_2 LFC_{t-i} + \lambda_3 LAR_{t-i} + \lambda_4 LAP_{t-i} \\ & + \lambda_5 LAT_{t-i} + \lambda_6 LCO_{2t-i} + \lambda_7 LRP_{t-i} + \lambda_8 LCR_{t-i} + \varepsilon_t \end{aligned} \tag{9}$$

$$\begin{aligned} \Delta LCR_t = & \delta_0 + \delta_1 \sum_{i=1}^p \Delta LCR_{t-1} + \delta_2 \sum_{i=1}^p \Delta LIS_{t-1} + \delta_3 \sum_{i=1}^p \Delta LFC_{t-1} \\ & + \delta_4 \sum_{i=1}^p \Delta LAR_{t-1} + \delta_5 \sum_{i=1}^p \Delta LAP_{t-1} + \delta_6 \sum_{i=1}^p \Delta LAT_{t-1} + \delta_7 \sum_{i=1}^p \Delta LCO_{2t-1} \\ & + \delta_8 \sum_{i=1}^p \Delta LRP_{t-1} + \lambda_1 LCR_{t-i} + \lambda_2 LIS_{t-i} + \lambda_3 LFC_{t-i} + \lambda_4 LAR_{t-i} \\ & + \lambda_5 LAP_{t-i} + \lambda_6 LAT_{t-i} + \lambda_7 LCO_{2t-i} + \lambda_8 LRP_{t-i} + \varepsilon_t \end{aligned} \tag{10}$$

In Equations (3)–(10), δ represents the intercept, $\delta_1, \dots, \delta_8$ denote the short-run parameters, $\lambda_1, \dots, \lambda_8$ represent the long-run parameters, and ε_t is the error term. This investigation used the ARDL

bounds method based on F-statistics to explore the LT cointegrating association among the variables. The current study tested the null hypothesis that there is no LT cointegration. If the F-statistic value is much higher than I(1) bound, then we can reject the null hypothesis, which means that LT cointegration exists among the variables. Once the LT cointegration between rice production, CO₂ emissions, temperature, precipitation, rice area, fertilizer consumption, improved seed, and agricultural credit is established, the LT and SHT associations between rice production and climatic and non-climatic variables can be scrutinised as follows [29,67,68,77].

$$\begin{aligned} \Delta LRP_t = & \delta_0 + \delta_1 \sum_{i=1}^p \Delta LRP_{t-1} + \delta_2 \sum_{i=1}^p \Delta LCO_{2t-1} + \delta_3 \sum_{i=1}^p \Delta LAT_{t-1} \\ & + \delta_4 \sum_{i=1}^p \Delta LAP_{t-1} + \delta_5 \sum_{i=1}^p \Delta LAR_{t-1} + \delta_6 \sum_{i=1}^p \Delta LFC_{t-1} + \delta_7 \sum_{i=1}^p \Delta LIS_{t-1} \\ & + \delta_8 \sum_{i=1}^p \Delta LCR_{t-1} + \varphi_1 ECT_{t-1} + \varepsilon_t \end{aligned} \tag{11}$$

$$\begin{aligned} \Delta LCO_{2t} = & \delta_0 + \delta_1 \sum_{i=1}^p \Delta LCO_{2t-1} + \delta_2 \sum_{i=1}^p \Delta LRP_{t-1} + \delta_3 \sum_{i=1}^p \Delta LAT_{t-1} \\ & + \delta_4 \sum_{i=1}^p \Delta LAP_{t-1} + \delta_5 \sum_{i=1}^p \Delta LAR_{t-1} + \delta_6 \sum_{i=1}^p \Delta LFC_{t-1} + \delta_7 \sum_{i=1}^p \Delta LIS_{t-1} \\ & + \delta_8 \sum_{i=1}^p \Delta LCR_{t-1} + \varphi_1 ECT_{t-1} + \varepsilon_t \end{aligned} \tag{12}$$

$$\begin{aligned} \Delta LAT_t = & \delta_0 + \delta_1 \sum_{i=1}^p \Delta LAT_{t-1} + \delta_2 \sum_{i=1}^p \Delta LCO_{2t-1} + \delta_3 \sum_{i=1}^p \Delta LRP_{t-1} \\ & + \delta_4 \sum_{i=1}^p \Delta LAP_{t-1} + \delta_5 \sum_{i=1}^p \Delta LAR_{t-1} + \delta_6 \sum_{i=1}^p \Delta LFC_{t-1} + \delta_7 \sum_{i=1}^p \Delta LIS_{t-1} \\ & + \delta_8 \sum_{i=1}^p \Delta LCR_{t-1} + \varphi_1 ECT_{t-1} + \varepsilon_t \end{aligned} \tag{13}$$

$$\begin{aligned} \Delta LAP_t = & \delta_0 + \delta_1 \sum_{i=1}^p \Delta LAP_{t-1} + \delta_2 \sum_{i=1}^p \Delta LAT_{t-1} + \delta_3 \sum_{i=1}^p \Delta LCO_{2t-1} \\ & + \delta_4 \sum_{i=1}^p \Delta LRP_{t-1} + \delta_5 \sum_{i=1}^p \Delta LAR_{t-1} + \delta_6 \sum_{i=1}^p \Delta LFC_{t-1} + \delta_7 \sum_{i=1}^p \Delta LIS_{t-1} \\ & + \delta_8 \sum_{i=1}^p \Delta LCR_{t-1} + \varphi_1 ECT_{t-1} + \varepsilon_t \end{aligned} \tag{14}$$

$$\begin{aligned} \Delta LAR_t = & \delta_0 + \delta_1 \sum_{i=1}^p \Delta LAR_{t-1} + \delta_2 \sum_{i=1}^p \Delta LAP_{t-1} + \delta_3 \sum_{i=1}^p \Delta LAT_{t-1} \\ & + \delta_4 \sum_{i=1}^p \Delta LCO_{2t-1} + \delta_5 \sum_{i=1}^p \Delta LRP_{t-1} + \delta_6 \sum_{i=1}^p \Delta LFC_{t-1} + \delta_7 \sum_{i=1}^p \Delta LIS_{t-1} \\ & + \delta_8 \sum_{i=1}^p \Delta LCR_{t-1} + \varphi_1 ECT_{t-1} + \varepsilon_t \end{aligned} \tag{15}$$

$$\begin{aligned} \Delta LFC_t = & \delta_0 + \delta_1 \sum_{i=1}^p \Delta LFC_{t-1} + \delta_2 \sum_{i=1}^p \Delta LAR_{t-1} + \delta_3 \sum_{i=1}^p \Delta LAP_{t-1} \\ & + \delta_4 \sum_{i=1}^p \Delta LAT_{t-1} + \delta_5 \sum_{i=1}^p \Delta LCO_{2t-1} + \delta_6 \sum_{i=1}^p \Delta LRP_{t-1} + \delta_7 \sum_{i=1}^p \Delta LIS_{t-1} \\ & + \delta_8 \sum_{i=1}^p \Delta LCR_{t-1} + \varphi_1 ECT_{t-1} + \varepsilon_t \end{aligned} \tag{16}$$

Table 1
Descriptive statistics and correlation analysis.

	LRP	LCO ₂	LAT	LAP	LAR	LFC	LIS	LCR
Panel A								
Mean	15.2198	7.9991	2.5332	4.6425	14.2102	10.7692	8.1667	8.0117
Median	15.2528	7.9522	2.5379	4.7068	14.2251	10.7581	8.1645	8.0561
Maximum	15.4700	9.1165	2.5950	4.9532	14.2602	12.6071	9.4319	9.2218
Minimum	14.7652	6.4526	2.4480	3.7871	14.0483	8.0574	7.4922	6.9225
Std. Dev.	0.1690	0.6260	0.0363	0.2133	0.0512	1.2635	0.5049	0.7740
Skewness	-0.7917	-0.3594	-0.3936	-2.3884	-1.4119	-0.4951	0.8375	0.1001
Kurtosis	3.5406	3.0829	2.9747	10.7053	4.8540	2.5656	3.1763	1.5273
Jarque-Bera	3.1496	0.5890	0.6980	92.4647	12.8387	1.3154	3.1914	2.4848
Probability	0.2070	0.7448	0.7053	0.0000	0.0016	0.5180	0.2027	0.2886
Sum	410.9371	215.9777	68.3987	125.3491	383.6761	290.7704	220.5028	216.3183
Sum Sq. Dev.	0.7431	10.1903	0.0343	1.18353	0.0681	41.5121	6.6302	15.5790
Observations	27	27	27	27	27	27	27	27
Correlation analysis								
Panel B								
LRP	1.0000							
LCO ₂	0.8451***	1.000						
LAT	0.6553***	0.5215***	1.0000					
LAP	0.1452	-0.0910	0.0596	1.0000				
LAR	0.5862***	0.2273	0.4703**	0.3942**	1.0000			
LFC	0.0852	0.3217	-0.2791	-0.0956	-0.4870**	1.0000		
LIS	0.4636**	0.5790***	0.1514	-0.3025	-0.1916	0.4351**	1.0000	
LCR	0.2830	0.3898**	-0.0518	0.0994	0.1892	0.3044	-0.0434	1.0000

**Shows the significance at 5% level.

***Shows the significance at 1% level.

$$\begin{aligned} \Delta LIS_t = & \delta_0 + \delta_1 \sum_{i=1}^p \Delta LIS_{t-i} + \delta_2 \sum_{i=1}^p \Delta LFC_{t-i} + \delta_3 \sum_{i=1}^p \Delta LAR_{t-i} \\ & + \delta_4 \sum_{i=1}^p \Delta LAP_{t-i} + \delta_5 \sum_{i=1}^p \Delta LAT_{t-i} + \delta_6 \sum_{i=1}^p \Delta LCO_{2t-i} + \delta_7 \sum_{i=1}^p \Delta LRP_{t-i} \\ & + \delta_8 \sum_{i=1}^p \Delta LCR_{t-i} + \varphi_1 ECT_{t-1} + \varepsilon_t \end{aligned} \tag{17}$$

$$\begin{aligned} \Delta LCR_t = & \delta_0 + \delta_1 \sum_{i=1}^p \Delta LCR_{t-i} + \delta_2 \sum_{i=1}^p \Delta LIS_{t-i} + \delta_3 \sum_{i=1}^p \Delta LFC_{t-i} \\ & + \delta_4 \sum_{i=1}^p \Delta LAR_{t-i} + \delta_5 \sum_{i=1}^p \Delta LAP_{t-i} + \delta_6 \sum_{i=1}^p \Delta LAT_{t-i} + \delta_7 \sum_{i=1}^p \Delta LCO_{2t-i} \\ & + \delta_8 \sum_{i=1}^p \Delta LRP_{t-i} + \varphi_1 ECT_{t-1} + \varepsilon_t \end{aligned} \tag{18}$$

where, ECT_{t-1} stands for the error correction term, which reports the adjustment speed of the LT equilibrium. This investigation applied many diagnostic approaches, including serial correlation and heteroskedasticity tests. The cumulative sum of recursive residuals (CUSUM) test was also used to check the fitness and stability of the ARDL model.

5. Results and discussions

5.1. Descriptive statistics and correlation analysis

Table 1 reports the results of descriptive statistics and correlation analysis. It shows that as per the Jarque-Bera test, LAP and LAR do not follow a normal distribution, whereas LRP, LCO₂, LFC, LIS, and LCR are normally distributed. However, the dilemma of normality can be resolved by adopting the ARDL technique. Further, Table 1 reveals that climatic and non-climatic factors are positively associated with rice production.

Table 2
Results of ADF and PP unit root tests.

Variables	ADF test		PP test	
	Level	1st Diff.	Level	1st Diff.
LRP	-4.8438***	-6.0448***	-4.8695***	-14.9300***
LCO ₂	-3.1532	-5.5369***	-3.1562	-5.5621***
LAT	-3.5452**	-5.7929***	-3.5088*	-14.8265***
LAP	-4.8151***	-2.6524	-4.6227***	-12.9124***
LAR	-3.5300**	-5.6935***	-3.4709*	-13.1882***
LFC	-1.5916	-6.5253***	-1.5354	-6.4114***
LIS	-1.8381	-4.3572**	-2.0126	-4.3810***
LCR	-1.6486	-4.6137***	-1.8184	-4.6137***

* Indicates stationarity at 10% significance level.

** Indicates stationarity at 5% significance level.

*** Indicates stationarity at 1% significance level.

5.2. Unit root test results

The investigation applied Augmented Dickey-Fuller (ADF) and Phillips-Perron tests to check the stationarity of the underlying variables. Table 2 demonstrates the outcomes of both the ADF and PP tests, indicating that LRP, LAT, and LAP are stationary at I(0), whereas LCO₂, LFC, LIS, and LCR are stationary at I(1). Thus, the results of both the ADF and PP tests suggest applying the ARDL model to explore the LR and SR associations among the selected variables.

5.3. Result of the long-run (LR) nexus

The current study utilised the ARDL bounds method to explore the LR interrelationships among the variables. The results in Table 3 indicate that there is a LR association that exists among the variables in interest when regression is normalised in the LRP, LCO₂, LAP, and LAR models. This means that the underlying variables are integrated.

We used the J-J cointegration technique with the trace statistic test (TST) and maximum eigenvalue test (MET) to further affirm the LT relationship between the variables. In Table 4, the J-J cointegration technique results revealed that there is also LT association among CO₂ emissions, temperature, precipitation, cultivated area, fertiliser

Table 3
ARDL Cointegrating results.

Estimated models	F-statistic	Cointegration exist
F _{LRP} (LRP/LCO ₂ , LAT, LAP, LAR, LFC, LIS, LCR)	11.0912***	Yes
F _{LCO₂} (LCO ₂ /LRP, LAT, LAP, LAR, LFC, LIS, LCR)	3.6782**	Yes
F _{LAT} (LAT/LCO ₂ , LRP, LAP, LAR, LIS, LFC, LCR)	3.1841	No
F _{LAP} (LAP/LAT, LCO ₂ , LRP, LAR, LIS, LFC, LCR)	4.5832***	Yes
F _{LAR} (LAR/LAP, LAT, LCO ₂ , LRP, LIS, LFC, LCR)	5.3881***	Yes
F _{LFC} (LFC/LAR, LAP, LAT, LCO ₂ , LRP, LIS, LCR)	0.8068	No
F _{LIS} (LIS/LFC, LAR, LAP, LAT, LCO ₂ , LRP, LCR)	2.2964	No
F _{LCR} (LCR/LIS, LFC, LAR, LAP, LAT, LCO ₂ , LRP)	1.5514	No
Significance	I0 Bound	I1 Bound
10%	2.38	3.45
5%	2.69	3.83
1%	3.31	4.63

**Depicts significance at 5% level.
***Depicts significance at 1% level.

Table 4
Johansen Cointegrating results.

Hypothesized	Eigenvalue	TST	0.05	Prob.
No. of CE(s)			Critical Value	
None *	0.9927	311.7654	159.5297	0.0000
At most 1 *	0.9425	188.6045	125.6154	0.0000
At most 2 *	0.8576	117.1862	95.75366	0.0008
At most 3	0.6912	68.44117	69.81889	0.0641
At most 4	0.5848	39.06239	47.85613	0.2578
At most 5	0.3390	17.08444	29.79707	0.6338
At most 6	0.2361	6.734389	15.49471	0.6087
At most 7	1.95E-0	0.000488	3.841466	0.9839
MST				
None *	0.9927	123.1608	52.3626	0.0000
At most 1 *	0.9425	71.4183	46.2314	0.0000
At most 2 *	0.8576	48.7450	40.0775	0.0042
At most 3	0.6912	29.3787	33.8768	0.1569
At most 4	0.5848	21.9779	27.5843	0.2215
At most 5	0.3390	10.3500	21.1316	0.7112
At most 6	0.2361	6.7339	14.2646	0.5211
At most 7	1.95E-0	0.0004	3.84146	0.9839

Trace test portrays three cointegrating eqn(s) at the 5% level of significance. Max-eigenvalue test portrays three cointegrating eqn(s) at the 5% level of significance.

* Portrays rejection of the hypothesis at the 5% level of significance.

consumption, improved seed, agricultural credit, and rice production in the context of Nepal. After proving the presence of LT cointegration linkage among the variables, we further proceeded by assessing the LR and SR effects of climate change on rice production in Nepal's context using the ARDL method.

5.4. Long-run (LR) and short-run (SR) estimates

The results of the LR and SR analyses are presented in Table 5. The estimated impact of climatic factors revealed that rice production (RP) declined by 0.13% when the concentration level of CO₂ emission (CO₂e) increased by a percentage in the LR. As reported by MoAD [19] in 2019, an area of approximately 39,239 ha of major food crops (rice, corn, and wheat), vegetables, fruits, and ponds for fisheries were affected by dry weather and flooding adversely. Warsame et al. [31] found that CO₂ emissions negatively affected crop production in both the SR and LR.

Table 5
LR and SR results based on the ARDL model (1, 1, 1, 0, 1, 1, 0).

Variables	Coefficient	Std. Error	t-Statistic	Prob.
Long-run analysis				
LCO ₂	-0.1353*	0.0745	-1.8161	0.0967
LAT	0.7241**	0.3292	2.1995	0.0501
LAP	0.0148	0.0587	0.2532	0.8047
LAR	2.2633***	0.4690	4.8256	0.0005
LFC	0.0569***	0.0162	3.5130	0.0049
LIS	-0.0316	0.0240	-1.3155	0.2151
LCR	0.0225	0.0128	1.7569	0.1067
C	-18.6116**	6.2200	-2.9921	0.0122
@TREND	0.0237***	0.0048	4.9481	0.0004
Short-run analysis				
DLRP(-1)	0.0203	0.1068	0.1899	0.8528
DLCO ₂	-0.0666	0.0629	-1.0593	0.3122
DLCO ₂ (-1)	-0.0659	0.0527	-1.2505	0.2371
DLAT	0.0695	0.2326	0.2989	0.7706
DLAT(-1)	0.6399**	0.2343	2.7304	0.0196
DLAP	-0.0548	0.0403	-1.3587	0.2014
DLAP(-1)	0.0694*	0.0373	1.8596	0.0899
DLAR	2.2173***	0.2633	8.4188	0.0000
DLFC	0.0254**	0.0100	2.5286	0.0280
DLFC(-1)	0.0303**	0.0098	3.0902	0.0103
DLIS	0.0322	0.0228	1.4134	0.1852
DLIS(-1)	-0.0632**	0.0276	-2.2863	0.0431
DLCR	0.0220	0.0122	1.7939	0.1003
@TREND	0.0232***	0.0036	6.4311	0.0000
CointEq(-1)	-0.9796***	0.1068	-9.1647	0.0000
R-squared	0.9902			
Adjusted R ²	0.9778			
F-statistic	79.883			
Prob(F-statistic)	0.0000			

*Exhibits significance at 10% level.
**Exhibits significance at 5% level.
***Exhibits significance at 1% level.

Many researchers have also reported that increasing the concentration level of CO₂ emissions in the atmosphere negatively influences agricultural production and causes food-security problems [71,78]. The estimated result is also in line with Ahmad et al. [29], who concluded that a 1% increase in the concentration level of CO₂ leads to a 0.62% decrease in agricultural production. Likewise, Qureshi et al. [43] showed that GHG emissions affected the production of major food crops severely, including wheat and rice in Pakistan.

Moving on to other climatic factors such as average temperature (AT) and average precipitation (AP), our findings show that 1% increase in AT and AP improves rice production by 0.72% and 0.01%, respectively, in the LR. In other words, we can conclude that RP increases owing to favourable weather conditions. The impact of the average temperature and average precipitation was comparable with those obtained in previous studies. Karn [61] found that a 1 °C increase in maximum temperature during the daytime through the ripening phase of rice improves harvest by 27 kg. ha⁻¹. However, the investigation also reports that production decreases when the day-time maximum temperature increases by 29.9 °C. Ammani et al. [79] revealed that annual precipitation significantly and positively contributes to maize production. Similar findings related to rainfall were also reported by Khan et al. [66], who found that rainfall improved maize production in Pakistan. Similarly, Anh et al. [76] observed that rainfall significantly contributed to agricultural productivity in the LR.

Further estimation of the impact of non-climatic factors revealed that RP boosts by 2.26%, 0.05%, and 0.02% when the cultivated area (AR), fertilizer consumption (FC), and formal credit (CR) increased by 1% in the LR. These results support earlier empirical studies [7,69,80–82]. In the context of Bangladesh, Das and Hossain [83] studied the impact of credit on rice production. They found that credit had a positive and significant influence on rice production. Similarly, Zhai et al. [69] found that fertiliser consumption influenced wheat yield positively in China.

Table 6
Results of diagnostic tests.

Tests	F-statistic	Prob.
ARCH LM	0.6446	0.4302
Ramsey RESET	1.7178	0.1166
Breusch-Godfrey	0.9840	0.3446

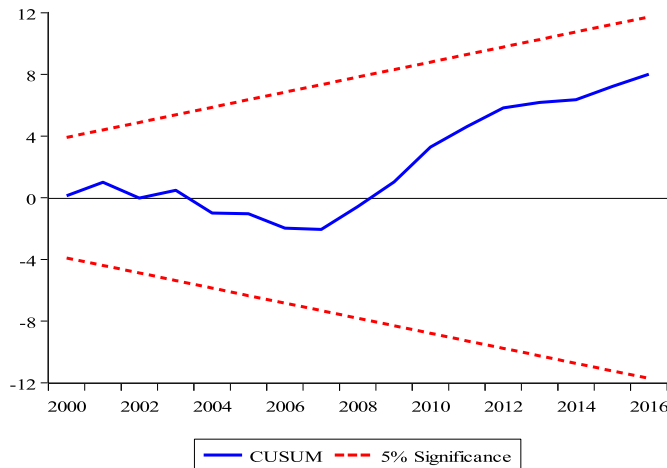


Fig. 7. CUSUM test.

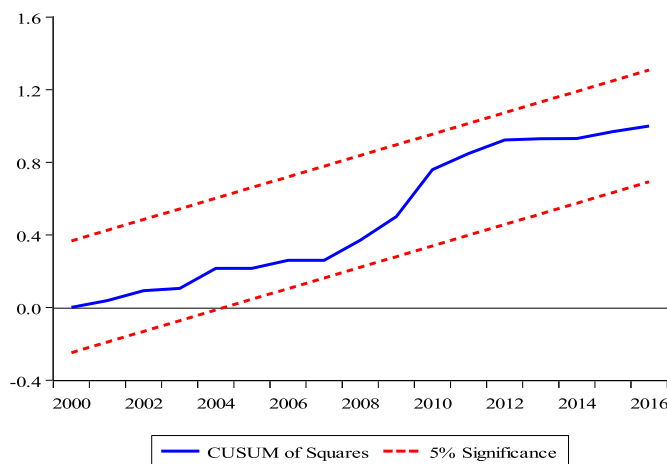


Fig. 8. CUSUM of squares test.

The estimated SR impact of climatic factors revealed that CO₂ decreased rice production by 0.066%, whereas AT enhanced rice production by approximately 0.069% in the SR. In contrast, AP also reduced rice production by 0.054% in the SR. Changes in climate caused by GHG emissions affect agricultural production directly or indirectly through the mean level of temperature, precipitation, and sunshine duration [84, 85]. Precipitation is one of the most crucial climatic factors and plays a crucial role in agriculture. Extreme precipitation has severe socio-economic effects in terms of its frequency and intensity [86,87]. Variability in precipitation affects agricultural production in different regions of the world. Changes in the mean amount of precipitation and temperature may lead to stronger droughts, which affects livestock and rainfed crop production negatively [88]. In addition, the estimated SR impact of non-climatic factors indicates that a 1% increase in AR, FC, IS, and CR will sustain rice production by 2.217%, 0.025%, 0.032%, and 0.022%, respectively. According to a report by MoAD [19], in Nepal, the agricultural sector's production has improved by 3.2%, while rice production has also significantly increased by 8.9% owing to the adoption of

improved seeds and a smooth supply of fertilisers and agricultural credit in the country.

5.5. Diagnostic tests results

To verify the ARDL model's fitness, the present study used the ARCH LM test for heteroskedasticity, Ramsey RESET test for functional misspecification, Breusch–Godfrey test for serial correlation CUSUM, and CUSUM of squares tests for constancy and stability of the estimated parameters. The findings of these diagnostic practices are demonstrated in Table 6, indicating that the ARDL model is correctly fitted while results of both CUSUM and CUSUM of squares tests (see Figs. 7 and 8), showing that the estimated LR and SR parameters of the model are stable over the time used in the study.

5.6. VAR Granger causality test results

The causality test using the VAR setup was applied to test the impact and direction of association among variables in the SR. The outcomes in Table 7 indicate unidirectional causality among cultivated areas, fertilisers, seeds, temperature, CO₂ emissions, and rice production. The results show that all these variables significantly influenced rice production in the SR. The values of the CO₂ emissions model describing that rice production, cultivated area, and fertilisers consumption enhances the level of emissions as a one-way connection is found among these variables. Rice production and precipitation are linked to rice production and fertiliser consumption. Similarly, unidirectional causality runs from rice production, emissions, fertilisers, and seeds to cultivated areas, and fertilisers are linked to area, credit availability, and rice production. The causality results for seeds confirm a one-way link running from precipitation rice production and cultivation area for the SR. Finally, unidirectional link is stable among the seeds, fertilisers, and credit availability. The study outcomes of Pickson et al. [67] also concluded that CO₂ emissions and temperatures negatively influences the cereal production significantly, while average precipitation, cultivated area, energy utilities, and labour significantly affects cereal production in China positively. The results further revealed unidirectional flow from CO₂ emissions, energy consumption, and labour to cereal production. Additionally, Chandio et al. [65] explored the effects of changes in CO₂ and institutional credit on agricultural production in Pakistan and revealed that in both the LR and SR periods, CO₂ emissions and institutional credit positively influenced agricultural production.

5.7. Impulse response function and variance decomposition method results

The impulse response function (IRF) was used to investigate the impact of the additional shocks of each variable on rice production. The outcomes of rice production shocks indicate a sudden decrease at the initial level; however, it continues steadily afterward. The shocks of CO₂ emissions are steady and increase at a balanced speed. The trends in average temperature also follow a similar pattern. However, variations could be seen in the response of the cultivation area, especially at the start. It became stable as time passed. Similarly, the impact of fertilisers was positive and stable. However, both seeds and credit facilities need improvements as the impact is not significant and is slightly negative with additional shocks. In summary, the impact of all variables is significant for rice production and this impact changes by additional time periods, confirming the causality results by showing similar trends (See Fig. 9).

Likewise, the impact of all variables on rice production was verified using the variance decomposition method (VDM) using 10 additional periods. The outcomes in Table 8 indicate that average temperature and CO₂ emissions are the most prominent factors contributing to rice production. Additionally, precipitation, seeds, and fertilisers also enhance rice productivity in the long run, as the impact of additional shocks

Table 7
Results of VAR Granger causality test.

Variables	LRP	LCO ₂	LAT	LAP	LAR	LFC	LIS	LCR
Wald-statistic (short-run causality)								
LRP	–	1.6100 (0.2045)	0.2090 (0.6475)	0.0955 (0.7572)	6.2497** (0.0124)	3.1334* (0.0767)	5.5074** (0.0189)	2.1859 (0.1393)
LCO ₂	10.0848*** (0.0015)	–	1.8869 (0.1695)	0.0381 (0.8451)	8.9901*** (0.0027)	2.7586* (0.0967)	1.2309 (0.2672)	1.8299 (0.1761)
LAT	2.8118* (0.0936)	1.3303 (0.2487)	–	0.1826 (0.6691)	0.8606 (0.3536)	0.0155 (0.9008)	0.0150 (0.9024)	0.0479 (0.8266)
LAP	0.2618 (0.6089)	2.0434 (0.1529)	0.0801 (0.7772)	–	0.3685 (0.5438)	0.0417 (0.8381)	1.8153 (0.1779)	0.1875 (0.6649)
LAR	1.2714 (0.2595)	0.4102 (0.5218)	0.6058 (0.4363)	0.5503 (0.4582)	–	1.5439 (0.2140)	6.9491*** (0.0084)	1.9983 (0.1575)
LFC	0.6283 (0.4280)	1.3352 (0.2479)	1.0797 (0.2988)	2.1859 (0.1393)	3.6327* (0.0567)	–	0.5118 (0.4743)	3.6469* (0.0562)
LIS	1.0978 (0.2947)	2.1914 (0.1388)	0.0451 (0.8317)	6.4617** (0.0110)	0.9620 (0.3267)	0.1605 (0.6886)	–	0.2162 (0.6419)
LCR	0.3321 (0.5644)	0.1578 (0.6912)	0.7917 (0.3736)	0.1452 (0.7031)	1.8546 (0.1732)	0.0702 (0.7910)	6.6631*** (0.0098)	–

* Reveals significance at 10% level.

** Reveals significance at 5% level.

***Reveals significance at 1% level.

Response to Generalized One S.D. Innovations ± 2 S.E.

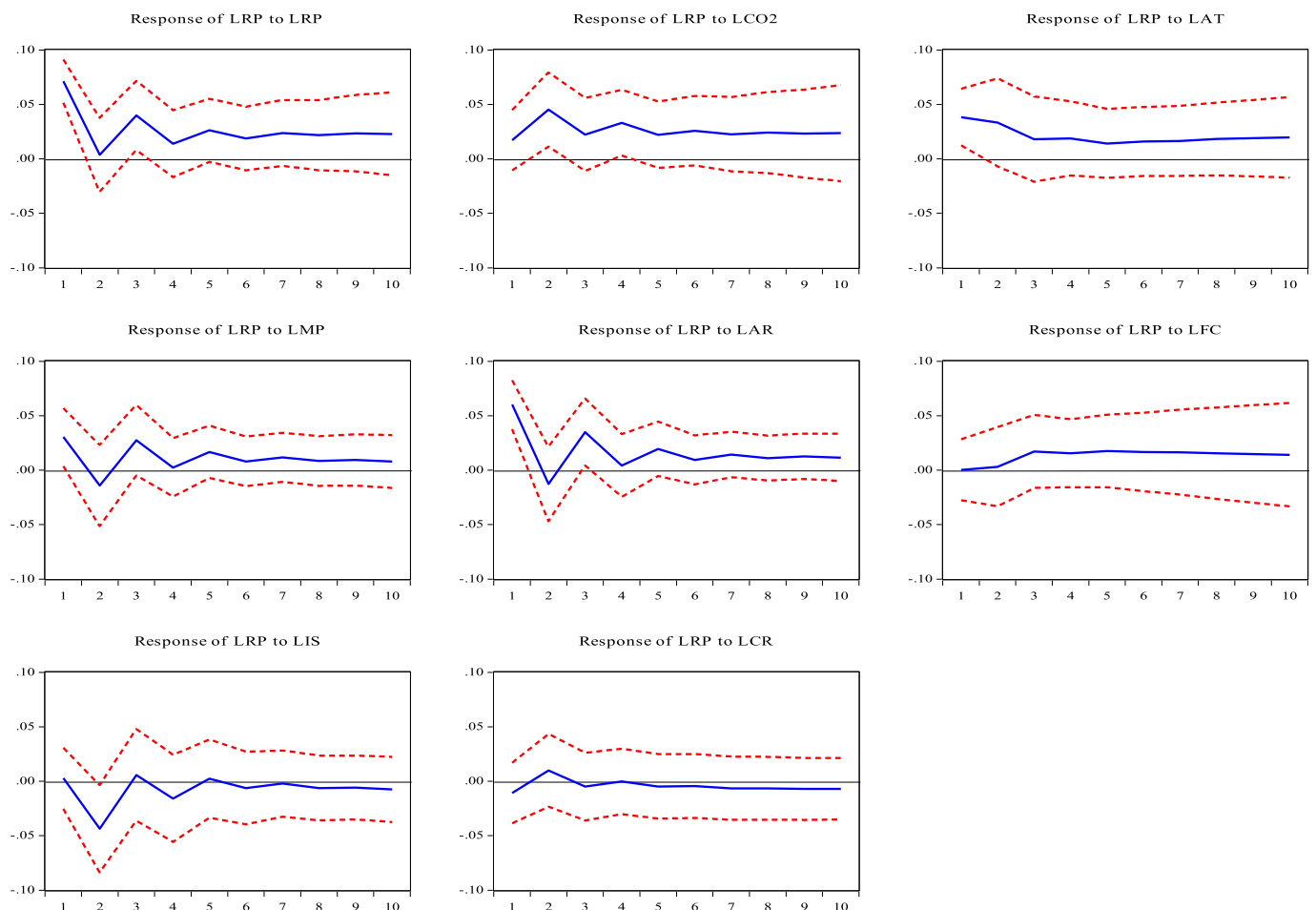


Fig. 9. Impulse response function.

become significant as time passes. These results support the main outcomes of previous techniques, indicating a substantial impact of climate and technological factors on rice production in Nepal. For example, climate change in developing countries has a more significant effect on agriculture compared to developed countries [45–48]. However, the

degree of influence depends on the extent of climate change and other variables [28]. Likewise, the decomposition of additional variables has also shown variations in the impact and a gradual increase in the effect of the variables. Therefore, both climate change and variations in technology trends are crucial for rice productivity in Nepal.

Table 8
VDM results.

Period	S.E.	LRP	LCO ₂	LAT	LAP	LAR	LFC	LIS	LCR
Variance Decomposition of LRP									
1	0.071	100.000	0.0000	0.000	0.000	0.000	0.0000	0.000	0.000
2	0.094	57.014	23.401	14.053	0.055	0.560	2.457	1.951	0.505
3	0.105	60.430	20.490	11.529	1.654	0.573	2.577	2.329	0.414
4	0.111	55.516	25.900	11.491	1.741	0.546	2.345	2.080	0.376
5	0.116	55.718	25.591	10.493	2.238	0.514	2.688	2.402	0.353
6	0.120	54.311	27.153	10.039	2.342	0.638	2.807	2.332	0.373
7	0.125	54.222	27.256	9.448	2.450	0.793	3.060	2.321	0.446
8	0.129	53.636	27.799	9.154	2.441	1.046	3.171	2.206	0.543
9	0.133	53.482	27.924	8.864	2.422	1.291	3.271	2.094	0.649
10	0.137	53.171	28.168	8.717	2.377	1.535	3.306	1.977	0.744
Variance Decomposition of LCO ₂									
1	0.148	5.735	94.264	0.000	0.000	0.000	0.000	0.000	0.000
2	0.206	25.864	61.563	0.026	5.143	0.576	2.332	4.256	0.236
3	0.254	31.055	54.000	0.329	5.321	1.151	4.116	3.654	0.370
4	0.297	35.405	48.383	0.741	4.854	1.850	5.051	3.077	0.635
5	0.334	37.799	45.132	1.395	4.361	2.590	5.273	2.547	0.900
6	0.369	39.822	42.537	1.984	3.946	3.160	5.279	2.132	1.136
7	0.401	41.151	40.792	2.598	3.597	3.588	5.145	1.814	1.311
8	0.430	42.216	39.475	3.107	3.331	3.875	4.986	1.577	1.429
9	0.457	42.990	38.550	3.534	3.127	4.064	4.826	1.399	1.505
10	0.481	43.611	37.859	3.865	2.974	4.184	4.688	1.261	1.554
Variance Decomposition of LAT									
1	0.030	28.707	0.091	71.200	0.000	0.000	0.000	0.000	0.000
2	0.032	28.714	0.218	65.087	0.022	1.764	2.124	0.318	1.748
3	0.033	27.334	0.548	62.561	0.217	2.388	4.620	0.342	1.986
4	0.033	26.854	0.533	60.858	0.219	2.994	5.900	0.579	2.059
5	0.033	26.410	0.547	59.890	0.230	3.403	6.765	0.665	2.086
6	0.034	26.148	0.543	59.264	0.231	3.723	7.221	0.774	2.091
7	0.034	25.974	0.540	58.866	0.233	3.932	7.523	0.838	2.089
8	0.034	25.860	0.550	58.601	0.234	4.078	7.694	0.892	2.086
9	0.034	25.797	0.561	58.420	0.235	4.172	7.805	0.923	2.083
10	0.034	25.757	0.581	58.291	0.237	4.234	7.873	0.944	2.079
Variance Decomposition of LAP									
1	0.188	18.124	2.198	9.306	70.370	0.000	0.000	0.000	0.000
2	0.238	14.332	14.019	10.429	45.179	1.000	1.629	13.209	0.199
3	0.245	14.430	13.656	10.462	42.535	1.208	1.800	12.840	3.066
4	0.251	14.197	13.124	11.100	41.251	1.798	1.760	12.518	4.248
5	0.254	14.680	12.750	11.426	40.247	2.061	1.831	12.303	4.698
6	0.257	14.781	12.547	11.938	39.490	2.136	1.993	12.275	4.837
7	0.259	14.954	12.449	12.173	39.076	2.126	2.119	12.243	4.857
8	0.259	14.991	12.437	12.306	38.861	2.114	2.224	12.220	4.843
9	0.260	15.018	12.439	12.335	38.772	2.119	2.282	12.198	4.833
10	0.260	15.020	12.447	12.338	38.733	2.133	2.313	12.185	4.828
Variance Decomposition of LAR									
1	0.029	71.084	3.774	1.186	1.690	22.264	0.000	0.000	0.000
2	0.039	51.658	10.170	7.185	1.474	16.248	9.163	1.671	2.427
3	0.043	42.127	10.991	10.597	2.028	18.810	7.961	4.208	3.273
4	0.046	43.200	9.954	9.986	1.857	19.175	7.994	4.214	3.616
5	0.047	40.888	10.519	11.466	1.827	19.195	7.431	5.099	3.570
6	0.048	41.347	10.471	11.556	1.754	18.940	7.232	5.187	3.508
7	0.049	40.966	11.024	11.879	1.704	18.670	7.044	5.285	3.424
8	0.050	41.156	11.301	11.850	1.695	18.434	6.968	5.228	3.365
9	0.050	41.132	11.699	11.831	1.696	18.240	6.911	5.168	3.319
10	0.050	41.216	11.968	11.749	1.713	18.069	6.891	5.107	3.282
Variance Decomposition of LFC									
1	0.794	0.001	23.088	5.768	7.455	1.049	62.636	0.000	0.000
2	0.966	2.006	17.019	6.375	6.178	4.132	63.600	0.538	0.149
3	1.063	2.840	16.333	5.324	5.738	8.282	60.889	0.467	0.123
4	1.160	6.804	15.452	4.476	5.193	10.702	56.700	0.399	0.269
5	1.250	9.888	16.116	4.449	4.592	12.311	51.652	0.540	0.448
6	1.333	13.423	16.592	4.565	4.148	12.944	47.105	0.630	0.589
7	1.408	16.142	17.482	4.902	3.804	13.078	43.192	0.716	0.680
8	1.475	18.593	18.289	5.137	3.565	12.909	40.035	0.733	0.735
9	1.535	20.547	19.145	5.332	3.394	12.626	37.464	0.720	0.768
10	1.589	22.236	19.902	5.443	3.275	12.299	35.361	0.688	0.792
Variance Decomposition of LIS									
1	0.293	0.150	18.673	9.852	0.009	0.403	2.457	68.451	0.000
2	0.340	1.106	13.978	9.838	0.574	3.080	2.418	61.837	7.164
3	0.390	12.087	11.064	7.900	0.564	5.272	2.604	47.294	13.211
4	0.438	16.942	10.889	10.335	0.804	6.940	2.072	37.883	14.131
5	0.477	21.952	10.808	11.641	0.767	7.210	1.769	32.201	13.648
6	0.508	24.414	11.725	12.909	0.709	7.027	1.627	28.768	12.817
7	0.529	26.441	12.575	13.371	0.652	6.723	1.527	26.594	12.113

(continued on next page)

Table 8 (continued)

Period	S.E.	LRP	LCO ₂	LAT	LAP	LAR	LFC	LIS	LCR
8	0.545	27.683	13.541	13.541	0.629	6.453	1.451	25.132	11.565
9	0.556	28.672	14.345	13.463	0.644	6.237	1.391	24.091	11.153
10	0.566	29.388	15.064	13.311	0.679	6.069	1.353	23.302	10.830
Variance Decomposition of LCR									
1	0.454	2.310	0.003	0.010	5.255	1.766	0.453	3.319	86.881
2	0.594	3.085	3.946	3.900	11.370	1.189	6.339	2.012	68.155
3	0.685	2.687	4.599	7.439	11.942	0.993	13.459	1.790	57.087
4	0.742	2.708	4.772	9.061	11.957	0.901	17.554	2.067	50.976
5	0.780	2.451	4.681	9.993	11.863	1.154	20.792	2.353	46.709
6	0.804	2.462	4.919	9.866	11.607	1.839	22.937	2.342	44.024
7	0.824	3.021	5.238	9.451	11.264	2.725	24.120	2.246	41.931
8	0.843	3.982	5.748	9.057	10.862	3.614	24.469	2.153	40.111
9	0.862	5.273	6.343	8.794	10.446	4.333	24.295	2.090	38.422
10	0.880	6.647	7.029	8.662	10.049	4.851	23.839	2.047	36.872

6. Conclusions

In South Asian countries, including Nepal, rice crop has a special importance and economic significance in agricultural growth and poverty reduction. Rice is widely grown, followed by maize and wheat, which are the leading staple foods of the Nepalese people. This study investigates how the effects of climate change and technological progress on rice production vary depending on the short-run and long-run in Nepal in the 1990–2016 period employing the ARDL approach. The findings indicate that in both the long- and short-run, the concentration level of CO₂ emissions influenced rice production adversely, while average temperature had no adverse effect on rice production. However, average precipitation improves rice production in the long run but deteriorates in short run. Further findings revealed that cultivated area, fertiliser consumption, and agricultural credit positively influences rice production positively in the long and short run. The causality results indicated a unidirectional causality among cultivated area, fertilisers, seeds, temperature, CO₂ emissions, and rice production, showing that all these variables have influenced rice production significantly in the short run. Additionally, both IRF and VDM confirmed the substantial impact of climate and technological factors on rice production and variations in Nepal.

These input factors play an active role in improving rice production in Nepal. However, compared to other South Asian countries, rice production is still low in Nepal, the most food-insecure country in the region. Nepal is also more vulnerable to climate change and variability in South Asia. To cope with climate change and adaptation strategies, this study suggests that there is a need to enhance the area under cultivation, improve the irrigation system, provide timely supply of agricultural credit to farmers at flexible interest rates, change planting dates, apply recommended doses of fertilisers, and diversify crop cultivation. Furthermore, environmental pollution affects rice production negatively; thus, steps should be taken to control CO₂ emissions seriously, adopt policies to reduce greenhouse gas emissions and facilitate the development of climate-resilient agriculture in the country.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Nomenclature

ARDL	Autoregressive Distributed Lag
VAR	Vector Autoregressive
ADF	Augmented Dickey-Fuller
PP	Phillips-Perron
RP	Rice Production
CO ₂ e	Carbon Dioxide Emission

AP	Average Precipitation
AT	Average Temperature
AR	Rice Area
CR	Credit
FC	Fertilizer Consumption
IS	Improved Seed
GDP	Gross Domestic Product
FDI	Foreign Direct Investment
GHGs	Greenhouse Gases
IPCC	Intergovernmental Panel on Climate Change
LR	Long-run
LT	Long-term
SR	Short-run
SHT	Short-term
TST	Trace Statistic Test
MST	Max-eigenvalue Statistic Test
ECT	Error Correction Term
TST	Trace Statistic Test
MET	Maximum Eigenvalue Test
VECM	Vector Error Correction Model
VDM	Variance Decomposition Method
IRF	Impulse Response Function
NLSSs	Nepal Living Standard Surveys
SA	South Asia
SSAF	South Asia and Sub Saharan Africa
MoAD	Ministry of Agriculture and Livestock Development

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