



Sustainable maize production and climatic change in Nepal: robust role of climatic and non-climatic factors in the long-run and short-run

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Abstract

Among all other leading challenges of this century, climate change affects people's livelihoods, particularly those residing in rural areas. This study is the first attempt to assess the Long-run (LR) and Short-run (SR) impacts of climatic factors, namely CO₂ emissions, temperature, and precipitation on maize production in Nepal from 1983 to 2016, with the incorporation of cultivated area, fertilizers use, and credit supply as important input factors of maize production. To analyze the time-series dataset, we applied the Autoregressive distributed lag (ARDL), Vector error correction model (VECM), Impulse response function (IRF), and Variance decomposition (VD) methodologies. The results reveal that CO₂ emissions and temperature decreased maize production in the short- and long-run while precipitation improved maize production in both cases. Also, cultivated area and fertilizers use significantly contributed to maize production in both periods. The results of the VECM causality indicate that rainfall and cultivated area have two-way causal associations with maize production. The CO₂ emissions and credit represent unidirectional causality with maize production in the short-run. Besides, all variables share a significant long-run connection. Finally, the IRF and VD outcomes suggested that the effects of climatic and non-climatic factors are consistent on maize production. The policies recommend that better environmental quality is crucial for sustainable maize production in Nepal.

Keywords Climate change · Maize production · Credit · ARDL framework · Nepal

Abbreviations

CC	Climate change
LR	Long-run
SR	Short-run
ARDL	Autoregressive distributed lag
VECM	Vector error correction model

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IRF	Impulse response function
VD	Variance decomposition
GDP	Gross domestic product
ADF	Augmented dickey-fuller test
PP	Phillips and perron test
CO ₂	Carbon emission
MP	Maize production
AR	Average rainfall
AT	Average temperature
MA	Maize area
FC	Fertilizers consumption
CR	Credit
ln	Natural log
B	Beta
α_0	Constant term

1 Introduction

Climate change (CC) is among the significant challenges of this century, which widely disrupts rural people's livelihood who predominantly depends upon agriculture for food (Ali & Erenstein, 2017; Pickson et al., 2021). They use unsustainable agricultural production practices (Rohila et al., 2017), which generate nearly 10 percent of the global carbon dioxide (CO₂) (EPA, 2019) and adversely affect agricultural production in developing countries (Mulungu et al., 2021; Pickson & Boateng, 2021). Resultantly, during the last two decades, the global share of agriculture value-added plummeted substantially except for Africa, where it ascended marginally from 14.3 to 15.8%. Contrary, in Oceania and Asia, it decreased from 4 to 2.9% and 10.26% to 7.16%, respectively, and remained below 2% in America and Europe. Figure 1a provides the regional timeline of agriculture value-added.

Likewise, temperature and rainfall (precipitation) are other critical factors impacting agricultural production practices (Agovino et al., 2019). A report by Lindsey and Dahlman (2021) illustrated an increase of 0.18 °C per decade in global temperature since 2000, and the UN (2020) concluded that the last decade (2010–2019) is the warmest in history. Similarly, during the last two decades, the global rainfall patterns also changed significantly (Kuttippurath et al., 2021)—increasing by 0.10 inches per decade. Figure 1b provides the global pattern of temperature and rain. These activities posited uncertainty to the global environment and agricultural production (NOAA, 2021). Another study by Warsame et al. (2021) testified both variables and reported that the temperature adversely impacts agriculture in both long- and short-run, while rainfall increases agricultural production in the long-run and impedes in the short-run.

Furthermore, the growing body of the literature on climatic effects collectively reports the negative impacts of agricultural activities, which posits a threat to food and water security, especially in developing countries (Ali, 2021; Aryal et al., 2019; Bandara & Cai, 2014; Brizmohun, 2019; Pickson & Boateng, 2021; Rehman et al., 2020). Besides, studies report that the impact of CC is higher in South Asian economics (Im et al., 2017; Tesfayeet al., 2017), where nearly one-fourth of the global population lives (World Bank, 2020). Among these economics, CC is increasingly visible in Nepal with chronic droughts (Karmakar et al., 2017), floods (Dewan & Tanvir, 2015; Pathak,

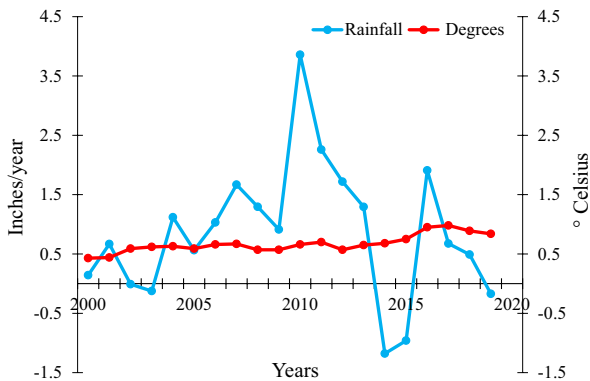
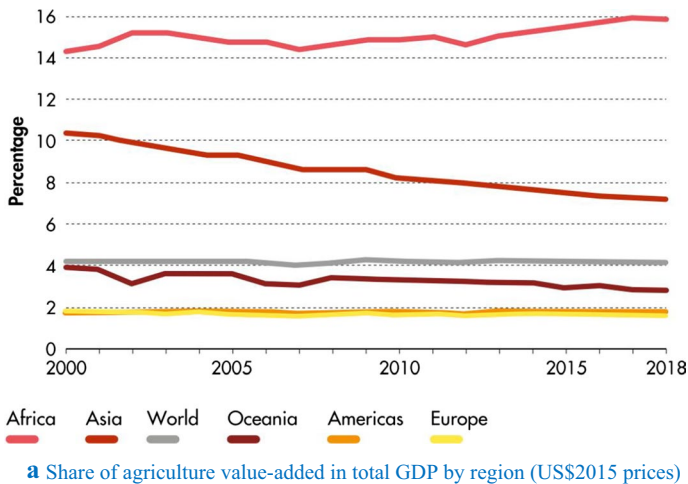


Fig. 1 **a** Share of agriculture value-added in total GDP by region (US\$2015 prices) (Source: (FAOSTAT, 2019)) **b** Global Land and Ocean Temperature and Precipitation Anomalies (Source : NOAA (2021))

2021), and heatwaves (Chung & Kim, 2014). The country experienced 180 events during 1999–2008, which caused a loss of 0.4% of GDP, despite its meager share in Global greenhouse gas (GHG) emissions.

More specifically, the Nepalese agricultural value-addition to the GDP decreased substantially from 37.1% to 27.7% during 2011–2020, which grew on an average of 3.2% during the last decade (MoAD, 2019). The food crop area also declined by 0.9% during the same period (MoF, 2019). Studies reported that several factors contribute to the decline of cultivated areas. For instance, land fragmentation, increase in housing demand, brain drain, and barren land (Van Nguyen & Ferrero, 2006). Besides, studies found that unpredictable and changing rainfall patterns, droughts, increased use of groundwater, and severe floods are the key factors severely affecting the farming practices in Nepal (Joshi & Joshi, 2019). Therefore, it is becoming a challenge to feed the population affected by climatic changes with reduced arable land and water availability (Rakshit et al., 2014).

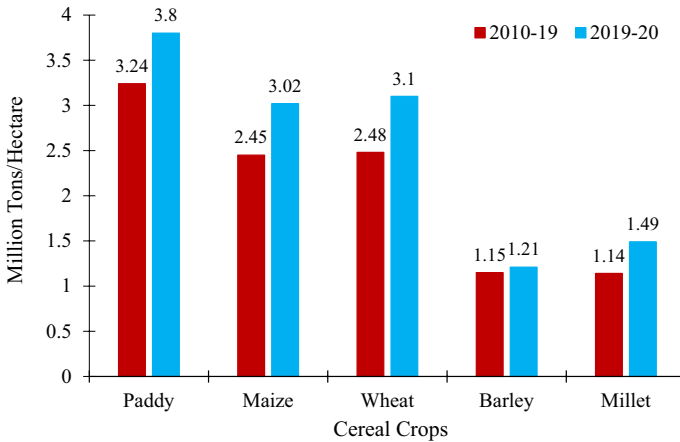


Fig. 2 Average productivity of cereal crops during the last decade (MT/ha). (Source: (MoF, 2019))



Fig. 3 Percentage change in production and productivity of Maize in Nepal. (Source: (MoF, 2019))

To feed its 20.14 million population (World Bank, 2020), Nepal significantly relies on cereal crops, such as paddy, maize, and wheat. In Nepal, maize is the second most important crop after paddy, with a total annual production of 2.8 million tons from 957.65 thousand hectares in 2019/20 (GoN, 2020). Figure 2 provides the per hectare productivity of the important cereal crops in Nepal during the last decade and 2020; maize ranks third highest in per hectare productivity (MoF, 2019). Despite the internal production, the country also imports maize (net importer) to meet the local demand. During 2019/20, it imported maize worth 1,183.2 rupees (in ten million).

Nevertheless, in Nepal, climatic factors including drought, late monsoon spell, rise in temperature, and flood severely affected maize production, especially during 2009–10, 2013, and 2015, as reported in Fig. 3 (MoF, 2019). In contrast, the average change in production and productivity after 2015 increased due to the efficient use of fertilizers, seeds, and advanced technologies (MoF, 2019). Besides, the maize crop is significantly affected

by natural disasters like floods, landslides, submersions, and cutting, especially in 2010, 2013, 2018, and 2020; in 2020, 15,023 hectares area of maize cultivation was affected by CC, which is the highest in the last ten years after 2013. Likewise, the impact is also among the highest in 2020, as shown in Fig. 4.

To offset the adverse impacts, the Nepalese agricultural sector made some crucial changes to increase the per hectare productivity (Khanal et al., 2018); in the last ten years, maize production grew from 2,067 thousand tons to 2,835 thousand tons. During the same time, the country also increased its annual fertilizer consumption from 110,013 metric tons to 394,595 metric tons (GoN, 2020). However, the credit supply to the agricultural sector merely increased (GoN, 2020). Factors include below 10 percent financing to the agricultural sector, despite the increase in the number of banks in Nepal (Vaidya, 2020). Another detailed report by GoP (2020) on agricultural census reported that merely 21.82% of farmers borrowed credit from the formal sector, whereas the remaining 78.18% either borrowed from informal/non-institutional sources or did not borrow.

Henceforth, to ensure the agricultural supply, mainly the maize production, to meet the country's growing cereal needs (food security), Nepal stringently needs to develop a firm policy to tackle raising CC, anomalies in temperature and rainfall, reduction in land area under cultivation, fertilizer consumption, and lower credit disbursement to the agricultural sector (Vaidya, 2020; Vij et al., 2018). To this end, the policymakers must know the impact of CC on agriculture, particularly maize production, as the rising temperature is a threat to food availability and the increase in GHGs, such as CO₂, chlorofluorocarbons (CFCs), nitrous oxide (N₂O), methane (CH₄), and Ozone (O₃) leads to rising temperatures. Studies on the climatic effects have widely reported the significantly negative impact of temperature on crop yields. For instance, wheat, maize, and rice yields reported a decline of 6%, 7.4%, and 3.2% during the past few years. Therefore, keeping in view the increasing climatic changes (Mulungu et al., 2021; Pickson & Boateng, 2021), deteriorating land productivity (Joshi & Joshi, 2019), and the importance of maize in meeting food security in particular to Nepal (FAO, 2021; Langner et al., 2019), it is of great concern for the researchers and policymakers to assess the influence of CC directly or indirectly on agricultural production (Aryal et al., 2019; Kogo et al., 2021; Rehman et al., 2020).

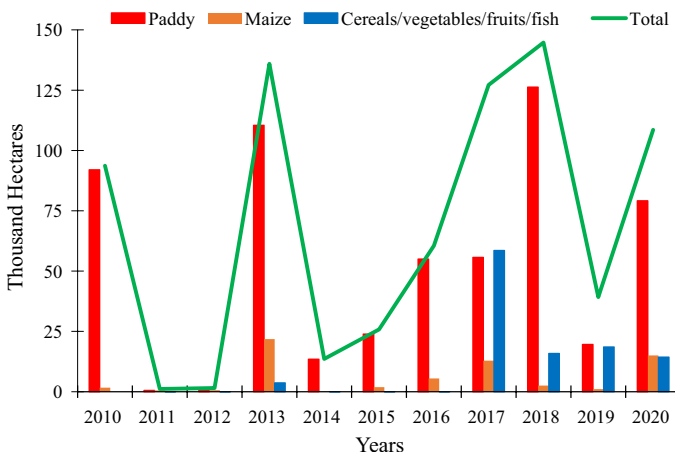


Fig. 4 Impact of natural disasters on the primary crop production area in Nepal. (Source: (MoF, 2019))

In the context of Nepal, several studies examined the impact of climatic changes on rice production (Chandio et al., 2021a; Devkota & Pajja, 2020; Rayamajhee et al., 2021), rice market integration and food security (Sanogo & Amadou, 2010), adoption of improved technologies (Ghimire & Huang, 2015, 2016; Ghimire et al., 2015; Kumar et al., 2020), social capital–food security nexus (Rayamajhee & Bohara, 2019), and determinants of flood adaptation (Pathak, 2021). However, to the best of the authors' knowledge, none of the studies combinedly assessed the impacts of climatic (CO₂ emission, rainfall, and temperature) and non-climatic factors (cultivated area, fertilizers use, and credit supply) on cereal (maize) production in the country. Therefore, the present study examines the Long-run (LR) and Short-run (SR) influences of climate change on maize production in Nepal. The study answers three key questions, including the impacts of climate change on maize production, the causal connection between climate change and maize production, and the role of non-climatic factors (i.e., cultivated area, fertilizers use, and credit supply) in improving maize production in the context of Nepal. The results reveal that CO₂ emissions and temperature decreased maize production in the long- and the short-run, while precipitation improved maize production in both cases. Along with, cultivated area and fertilizers use significantly contributed to maize production in both periods. Therefore, both hypotheses are fulfilled. Thus, the present work can be used as a reference for developing nations of similar economic and climatic features.

The contribution of the present study is fourfold; firstly, to the best of the authors' knowledge, this is the first attempt to assess the effects of CC factors, namely CO₂ emissions, temperature, and precipitation, on maize production in the case of Nepal. Secondly, the study undertakes the impacts of climatic as well as other non-climatic factors such as maize area, fertilizers use, and credit supply on maize production. Thirdly, most robust econometric approaches, i.e., the ARDL, VECM-Granger causality, IRF, and VDM, are used to get more reliable outcomes. Lastly, the study provides important insights for Nepalese policymakers to reduce their dependence on imported maize and increase internal production by incorporating the study results. Besides, the present work can be used as a reference for developing nations of similar economic and climatic features. Besides ensuring food security or preparing farmers for the continuously changing climate, the present study has provided a thorough investigation and practical policy implications.

The organization of the present study is as follows. The following section discusses the critical literature review, and the third section deals with methodology and data sources. The subsequent section provides and elaborates the empirical findings, and the fifth section concludes the whole investigation by providing the policy implications.

2 Literature review

Climate change (CC) directly and catastrophically impacts the farming yield as it widely relies on the weather (Abbas, 2020, 2021; Msowoya et al., 2016), and the concentration of CO₂ adversely affects crop production (Casemir & Diaw, 2018). The efforts undertaken for the sustainable food system suffer from the stern challenge of CC (Ali et al., (2020). The impacts of CC are determined through the precipitation levels, temperature patterns, weather resistance of crop varieties, income per capita, employability pattern by the agricultural sector, and economic activity generated (Benhin, 2006). Several researchers, for instance, Tao et al. (2006); You et al. (2009); Özdoğan (2011); Deressa et al. (2011); Tao et al. (2012); Potgieter et al. (2013); Fatuase and Ajibefun (2014); and Gmann and Horst

(2015) show the CC as the threat to the farming, water, and food, particularly in the developing nations. Cereal crops in South Asia are already facing the effects of CC; thus, studies conclude the negative influence of CC on agricultural production.

Multiple studies have identified the negative association between CC and agricultural produce worldwide and reinforced the farming sector's susceptibility to the CC. The developing nations in Asia, Africa, Latin America, and Oceania are exceedingly affected by the CC (Ding et al., (2017). Raymundo et al. (2018) excerpt that the increasing temperature and level of CO₂ in the air can decrease potato production and expects to reduce 6% by 2055 and 26% by 2085. Parry et al. (2007) further point that the effect of change in climate on the farms differs from region to region, i.e., temperate regions may see the positive impact of global warming (an increase in temperate by 1–3 °C), and tropical regions may see the negative impact of global warming. Sarker et al. (2014) prove that the mean maximum temperate negatively affect rice production, and the mean minimum temperature supports rice production.

Similar empirical studies on the effects of CC on agriculture point out that food production and its consumption increase greenhouse gases and negatively affect crops yields (Shi et al., 2018). Ruskiewicz et al. (2019) and Lu et al. (2019) state that climatic changes disrupt the quality and quantity of water which influences food production. Xie et al. (2018) predict that, by 2050, the CC can decrease the wheat produce by 9.4%. Sossou et al. (2019) explore the effect of CC on the yield of cereals. The results show the negative influence of temperature on cereal production and yield, and precipitation positively affects it. For instance, an increase in 1-mm rain can improve the production of cereals by 385 tons and yield by 9 kg/ha.

Ali et al. (2020) explored the relationship of crops (maize, rice, wheat), CC (via rainfall, temperature), and technical development (via agricultural machinery and fertilizers) during 1989–2015 in Pakistan. The results provide the negative influence of temperature and area and the positive influence of fertilizer on wheat yield. In contrast, rainfall negatively impacts the rice crop. Thus, the authors confirm the moderately negative impact of CC (rainfall, temperature) on crop yields (maize, rice, and wheat). Based on the results, the authors suggest developing adaptive policies, improved, high-yielding, and disease-resistant varieties, and enhanced irrigation for the agricultural sector to mitigate the effects of CC.

Zhai et al. (2017) investigate the impact of farmers' technical progress and CC on wheat production based on 1970–2014 data in Henan, China. The results provide the LR positive impact of machinery and fertilizer on wheat yield. For instance, the 1% surge in machinery and fertilizer is expected to increase the 0.21% and 0.19% wheat yield, respectively. In contrast, the rainfall during the emergence to maturity of wheat crops decreases wheat per unit area yield. In the short-run, this impact is negative, whereas the land size is positive on wheat yield. In comparison, the temperature has no impact on the yield of wheat.

Likewise, the study provides the weak impact of CC on wheat yield; however, there is evidence that the technical progress of farmers plays a significant role in improving the per unit area yield of wheat. Based on the results, the authors suggest designing well-positioned adaptive policies to tackle the future effects. Zhang and Yao (2013) excerpt that the CC has benefitted the Chinese northern and central region, yet the temperature effects are overall negative on wheat yield. Additionally, the rainfall, temperature, and solar radiations have decreased the wheat yield during 1981–2009 in South China and increased in the counterpart (Tao et al., (2014).

Pickson et al. (2020) investigate the effect of CC on the Chinese production of cereals using the quarterly data of 1990–2013. The results provide the long-run negative

effects of carbon dioxide, mean temperature, and variability in temperature on cereals production. Whereas mean rainfall, energy utilization, cultivated area, and labor force positively impact cereals production. Results further provide the evidence of Granger causality: a one-directional causality from carbon dioxide, labor force, and energy usage to cereals production. Based on the results, the authors suggest developing improved varieties of cereals to tackle the adverse impact of climate.

Zaied and Cheikh (2015) examine the Short-run (SR) and Long-run (LR) effects of CC on the agricultural sector of Tunisia. In the LR, the authors report the negative impact of increasing temperature on cereal and date production. Besides, there is a positive impact of precipitation on cereal production. In particular to Nepal, Pender and Hazell (2000) and Phukan et al. (2007) provide that the owing to the mountainous terrain, inadequate market infrastructure, lack of market access, and disproportionate dependency on the subsistence level of agriculture place Nepal among the counties widely hit by the CC. Rayamajhee et al. (2020) explore the impact of CC on rice production by using panel data from 2003 to 2010. The findings report the negative impact of CC on rice production. For instance, the 1 °C surge in temperature is expected to decrease rice production by 4.1 metric tons. Despite no evidence of the linkage between precipitation and rice production, high levels of rainfall reduce rice production. The results further report that most farmers use technically inefficient farming practices; farmers near roads and rivers are technically efficient. The authors suggest improving irrigation and providing farmers with market access to adapt to climatic changes.

Shrestha and Nepal (2016) suggest that the subsistence-level farmers, in Nepal particularly, are hit by CC. Authors explore the food security condition of vegetable-based and cereal-based subsistence-level farmers in Nepal using the data of 1980–2009. The results suggest that owing to the impact of CC, farmers have amended the conventional cropping patterns, crop varieties. They have increased the pesticides and fertilizers to maintain crop yields. Nevertheless, productivity is declining gradually, and only 33% of the farmers in the area are found to be food secure; vegetable-based farmers are more food secure than cereal-based. Based on the results, the authors suggest that the policies related to rainwater harvesting, planting colander adjustment, mulching, off-farm support, and opportunities may support farmers tackling CC. Ghimire and Huang (2015) determined the probability of adopting improved rice varieties by small farmers in Nepal using the cross-sectional data of 2013. The probit model results suggest the significant roles of extension services, education level, and access to seeds for the adoption decision of improved rice varieties. Likewise, farm size, favorable land, and animal type are also the primary factors influencing the probability of adoption decision.

Suvedi et al. (2017) investigate the variables impacting the participation of farmers in the agricultural extension programs and the adoption of improved varieties of seeds in Nepal. The results provide evidence that the adoption decisions are primarily influenced by the variables related to agricultural extension, i.e., training, farmers' membership in their groups, and off-farm employment of farmers. Likewise, these variables were influenced by the variables related to socioeconomic, i.e., education, age, distance to the extension office, and household size. Kumar et al. (2020) investigate the factors that define the Adoption and diffusion of improved technologies (ADITs) and Agricultural production practices (APP) and the effect of mediations on crop productivity and irregularity within the country. The results of the detailed study provide that the improved access to the markets, the involvement of the private sector for information dissemination and the sales of seeds, membership of farmers' groups and cooperative societies,

involvement in training programs, access to the credit facilities, and subsidies for seeds significantly improve the adoption and practices of improved technologies.

Rayamajhee and Bohara (2019) examine the association of farmers' engagement in voluntary associations and the intensity of community groups with food security in Nepal. The authors provide that the social capital (farmers' engagement in voluntary associations and intensity of community groups) can combat food insecurity. Results further suggest the direct impact of farmers' involvement in finance-related associations on hunger mitigation, whereas social capital may have environmental effects that can lead to positive food security management. Ghimire and Huang (2016) investigate the adoption of Modern rice varieties (MRVs) and their influence on the welfare of rural households in Nepal. The results postulate the significantly positive impact of MRVs on the income of rural households. In contrast, the distance from the market to the farmer's house negatively impacts. Likewise, the adoption decision is expounded by the education and age of the household head, access to the rice seeds, and extension services. Based on the findings, the authors suggest that owing to the transportation cost, distance to market, and other difficulties, seed availability in nearby markets will benefit farmers.

In particular to Maize, Khan et al. (2019) report that the maize crop is among those crops adversely facing the impact of CC. The authors explore the CC impact on maize production in the Pakistani province of Khyber Pakhtunkhwa by employing the climatic and non-climatic factors between 1996 and 2015. The results provide the negative effect of maize on yield. The authors suggest developing environment-resistant maize varieties and awareness among the maize farmers.

Previous literature is based on time-series and survey dataset with several approaches. However, none of previous reviewed studies employed the Vector error correction model (VECM), to check the short-run and long-run causality between the variables. This study also applied the IRF and the VDM to check the reliability and stability of the VECM. This study takes the advantage of these techniques by filling this gap and conducting an empirical work to assess the impacts of climate change on maize production in the context of Nepal. Additionally, this study can be used as a base of other developing nations in Asia with similar economic and climatic conditions to deal with food security. This makes the current investigation worthwhile not only for Nepal but also for other agriculture-based economy. Furthermore, based on the literature, the following connections are hypothesized:

H1 Climate change adversely affects maize production in the context of Nepal.

H2 Land area, fertilizers use, and credit supply enhance maize production in the context of Nepal.

3 Methodological framework

3.1 The data

This study empirically investigates the Climate change (CC) effects (via CO₂ emissions, temperature, and rainfall) on maize production in the Short-run (SR) and Long-run (LR), while including other non-climatic factors like maize area, fertilizers use, and credit by using yearly time-series data from 1983 to 2016. In this study, maize production is

measured in (tons), maize area is measured in (hectares), and fertilizers use is measured in (tons). The data of these variables are extracted from FAOSTAT (2019). Similarly, the CO₂ emission is measured in (kt), the average rainfall is measured in (mm), the average temperature is measured in (°C), and credit to the private sector by financial institutions (banks) is measured as (% of GDP). The data for these variables are retrieved from World Development Indicator (2019). The detailed descriptive statistics of the study variables are provided in Table 1. The present study ascertains the summary statistics of our main variables from 1983 to 2016 through box plots (see Fig. 5). Figure 6 shows the trend of the analyzed variables, while Fig. 7 displays the research methodology.

3.2 Model specification

In this study, the influence of climatic factors on maize production, we followed the model specification of Ahmad et al. (2020), Kumar et al. (2021), Pickson et al. (2020), and Warsame et al. (2021), who used climatic factors including CO₂ emissions, temperature, and rainfall in their model. In addition, this study also examines the effect of non-climatic factors such as maize area, fertilizers use, and credit on maize production; the generalized econometric model is expressed as follows:

$$MP_t = \alpha_0 + \beta_1 CO_{2t} + \beta_2 AR_t + \beta_3 AT_t + \beta_4 MA_t + \beta_5 FC_t + \beta_6 CR_t + \varepsilon_t \quad (1)$$

All study variables are transformed into the natural logarithmic form, and Eq. 1 is presented as follows:

$$\ln(MP_t) = \alpha_0 + \beta_1 \ln(CO_{2t}) + \beta_2 \ln(AR_t) + \beta_3 \ln(AT_t) + \beta_4 \ln(MA_t) + \beta_5 \ln(FC_t) + \beta_6 \ln(CR_t) + \varepsilon_t \quad (2)$$

In Eq. 2, $\ln MP$, $\ln CO_2$, $\ln AR$, $\ln AT$, $\ln MA$, $\ln FC$, and $\ln CR$ show the natural logarithmic of maize production, CO₂ emissions, temperature, rainfall, maize area, fertilizers use, and credit. ε_t is the error term, α_0 stands for the constant term, and $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$, and β_6 signify the LR coefficients.

Following the method of several researchers (Ahmad et al., 2020; Ahsan et al., 2020; Chandio, Magsi, et al., 2020; Warsame et al., 2021), the ARDL bounds testing method and ECM based on the ARDL practice advanced by Pesaran et al. (2001) is applied to investigate the LR and SR connections between CO₂ emissions, temperature, rainfall, maize area, fertilizers use, credit, and maize production in the context of Nepal. The ARDL is a more advantageous

Table 1 Descriptive statistics

	LnMP	LnCO ₂	LnAR	LnAT	LnMA	LnFC	LnCR
Mean	14.173	7.714	4.665	2.524	13.574	10.423	3.203
Median	14.145	7.870	4.711	2.524	13.605	10.783	3.265
Maximum	14.641	9.116	4.953	2.595	13.741	11.569	4.389
Minimum	13.542	6.204	3.787	2.447	13.129	7.569	2.067
Std. Dev	0.303	0.800	0.196	0.039	0.135	1.070	0.676
Skewness	-0.329	-0.198	-2.692	-0.214	-1.573	-1.417	-0.023
Kurtosis	2.313	2.068	12.897	2.551	5.254	3.996	1.861
Observations	34	34	34	34	34	34	34

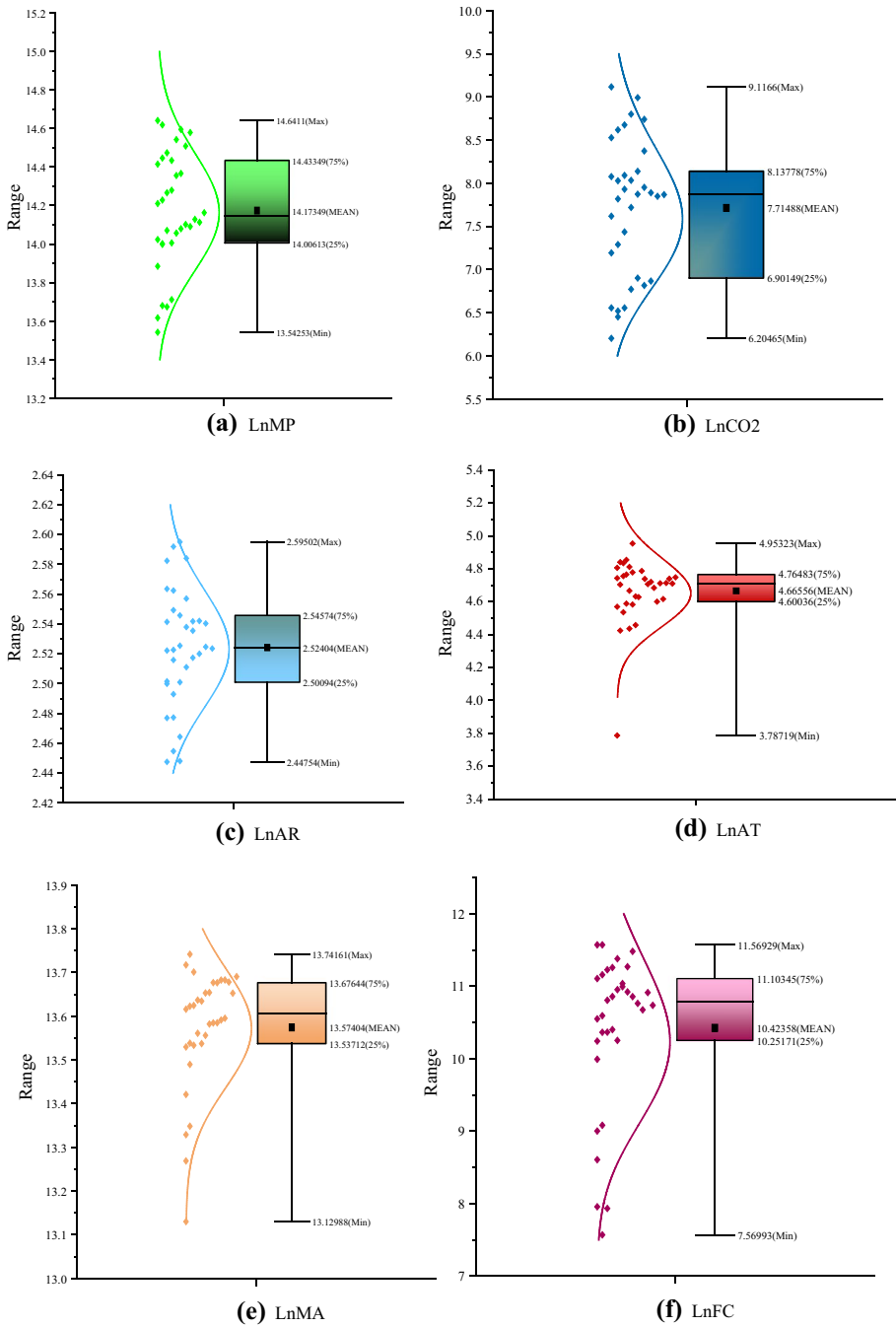


Fig. 5 Box-plot summary statistics of variables under consideration. **A** LMP, **b** LnCO₂, **c** LnAR, **d** LnAT, **e** LnMA, **f** LnFC, **g** LnCR

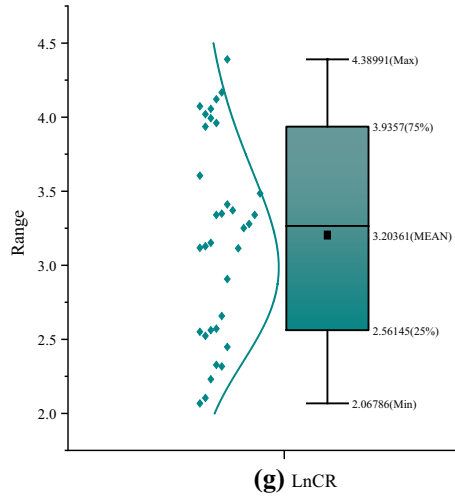


Fig. 5 (continued)

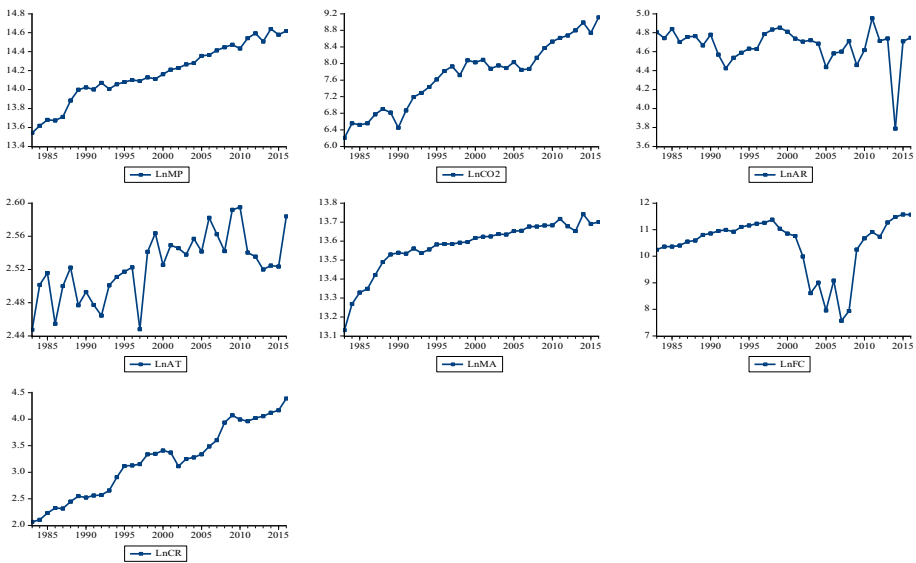


Fig. 6 Time-series trend of the analyzed variables

technique for small sample size than conventional cointegration methods, i.e., Engle and Granger (1987) and Johansen and Juselius (1990) tests. Further, when we have a mixture of the $I(0)$ and $I(1)$ series, the ARDL approach can be applied. However, it is not applicable when one of the study variables integrate at $I(2)$. Hence, this study carry-out the bounds test based on the following equations:

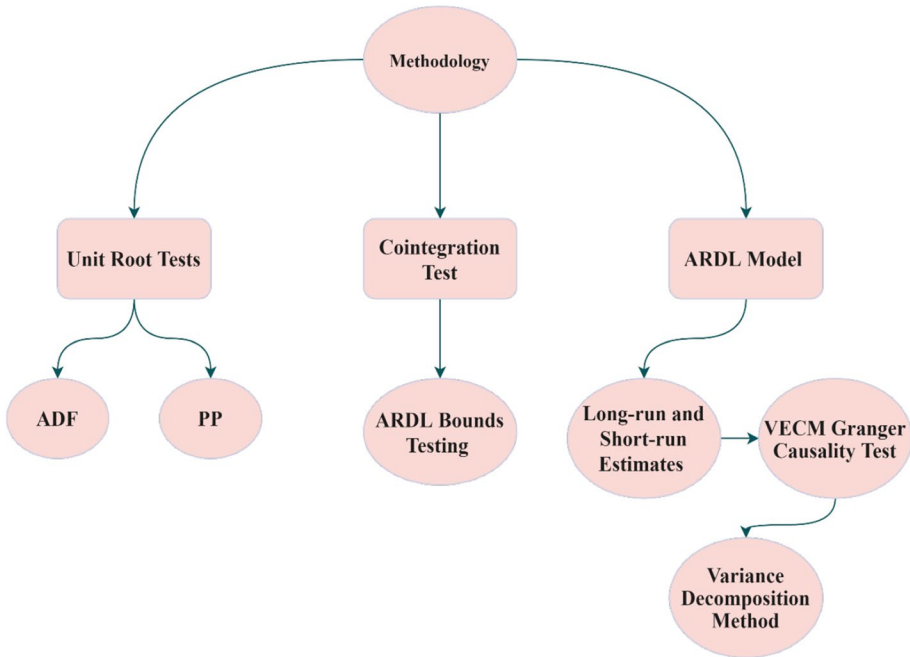


Fig. 7 Diagram of the research methodology

$$\begin{aligned}
 \Delta \ln MP_t = & Y_0 + \sum_{i=1}^p Y_1 \Delta \ln MP_{t-i} + \sum_{i=1}^q Y_2 \Delta \ln CO_{2t-i} + \sum_{i=1}^q Y_3 \Delta \ln AR_{t-i} + \sum_{i=1}^q Y_4 \Delta \ln AT_{t-i} \\
 & + \sum_{i=1}^q Y_5 \Delta \ln MA_{t-i} + \sum_{i=1}^q Y_6 \Delta \ln FC_{t-i} + \sum_{i=1}^q Y_7 \Delta \ln CR_{t-i} + \beta_1 \ln MP_{t-1} + \beta_2 \ln CO_{2t-1} \\
 & + \beta_3 \ln AR_{t-1} + \beta_4 \ln AT_{t-1} + \beta_5 \ln MA_{t-1} + \beta_6 \ln FC_{t-1} + \beta_7 \ln CR_{t-1} + \varepsilon_t
 \end{aligned} \tag{3}$$

$$\begin{aligned}
 \Delta \ln CO_{2t} = & Y_0 + \sum_{i=1}^p Y_1 \Delta \ln CO_{2t-i} + \sum_{i=1}^q Y_2 \Delta \ln MP_{t-i} + \sum_{i=1}^q Y_3 \Delta \ln AR_{t-i} + \sum_{i=1}^q Y_4 \Delta \ln AT_{t-i} \\
 & + \sum_{i=1}^q Y_5 \Delta \ln MA_{t-i} + \sum_{i=1}^q Y_6 \Delta \ln FC_{t-i} + \sum_{i=1}^q Y_7 \Delta \ln CR_{t-i} + \beta_1 \ln CO_{2t-1} + \beta_2 \ln MP_{t-1} \\
 & + \beta_3 \ln AR_{t-1} + \beta_4 \ln AT_{t-1} + \beta_5 \ln MA_{t-1} + \beta_6 \ln FC_{t-1} + \beta_7 \ln CR_{t-1} + \varepsilon_t
 \end{aligned} \tag{4}$$

$$\begin{aligned}
 \Delta \ln AR_t = & Y_0 + \sum_{i=1}^p Y_1 \Delta \ln AR_{t-i} + \sum_{i=1}^q Y_2 \Delta \ln CO_{2t-i} + \sum_{i=1}^q Y_3 \Delta \ln MP_{t-i} + \sum_{i=1}^q Y_4 \Delta \ln AT_{t-i} \\
 & + \sum_{i=1}^q Y_5 \Delta \ln MA_{t-i} + \sum_{i=1}^q Y_6 \Delta \ln FC_{t-i} + \sum_{i=1}^q Y_7 \Delta \ln CR_{t-i} + \beta_1 \ln AR_{t-1} + \beta_2 \ln CO_{2t-1} \\
 & + \beta_3 \ln MP_{t-1} + \beta_4 \ln AT_{t-1} + \beta_5 \ln MA_{t-1} + \beta_6 \ln FC_{t-1} + \beta_7 \ln CR_{t-1} + \varepsilon_t
 \end{aligned} \tag{5}$$

$$\begin{aligned} \Delta \ln AT_t = & Y_0 + \sum_{i=1}^p Y_1 \Delta \ln AT_{t-i} + \sum_{i=1}^q Y_2 \Delta \ln AR_{t-i} + \sum_{i=1}^q Y_3 \Delta \ln CO_{2t-i} + \sum_{i=1}^q Y_4 \Delta \ln MP_{t-i} \\ & + \sum_{i=1}^q Y_5 \Delta \ln MA_{t-i} + \sum_{i=1}^q Y_6 \Delta \ln FC_{t-i} + \sum_{i=1}^q Y_7 \Delta \ln CR_{t-i} + \beta_1 \ln AT_{t-1} + \beta_2 \ln AR_{t-1} \quad (6) \\ & + \beta_3 \ln CO_{2t-1} + \beta_4 \ln MP_{t-1} + \beta_5 \ln MA_{t-1} + \beta_6 \ln FC_{t-1} + \beta_7 \ln CR_{t-1} + \varepsilon_t \end{aligned}$$

$$\begin{aligned} \Delta \ln MA_t = & Y_0 + \sum_{i=1}^p Y_1 \Delta \ln MA_{t-i} + \sum_{i=1}^q Y_2 \Delta \ln AT_{t-i} + \sum_{i=1}^q Y_3 \Delta \ln AR_{t-i} + \sum_{i=1}^q Y_4 \Delta \ln CO_{2t-i} \\ & + \sum_{i=1}^q Y_5 \Delta \ln MP_{t-i} + \sum_{i=1}^q Y_6 \Delta \ln FC_{t-i} + \sum_{i=1}^q Y_7 \Delta \ln CR_{t-i} + \beta_1 \ln MA_{t-1} + \beta_2 \ln AT_{t-1} \quad (7) \\ & + \beta_3 \ln AR_{t-1} + \beta_4 \ln CO_{2t-1} + \beta_5 \ln MP_{t-1} + \beta_6 \ln FC_{t-1} + \beta_7 \ln CR_{t-1} + \varepsilon_t \end{aligned}$$

$$\begin{aligned} \Delta \ln FC_t = & Y_0 + \sum_{i=1}^p Y_1 \Delta \ln FC_{t-i} + \sum_{i=1}^q Y_2 \Delta \ln MA_{t-i} + \sum_{i=1}^q Y_3 \Delta \ln AT_{t-i} + \sum_{i=1}^q Y_4 \Delta \ln AR_{t-i} \\ & + \sum_{i=1}^q Y_5 \Delta \ln CO_{2t-i} + \sum_{i=1}^q Y_6 \Delta \ln MP_{t-i} + \sum_{i=1}^q Y_7 \Delta \ln CR_{t-i} + \beta_1 \ln FC_{t-1} + \beta_2 \ln MA_{t-1} \\ & + \beta_3 \ln AT_{t-1} + \beta_4 \ln AR_{t-1} + \beta_5 \ln CO_{2t-1} + \beta_6 \ln MP_{t-1} + \beta_7 \ln CR_{t-1} + \varepsilon_t \quad (8) \end{aligned}$$

$$\begin{aligned} \Delta \ln CR_t = & Y_0 + \sum_{i=1}^p Y_1 \Delta \ln CR_{t-i} + \sum_{i=1}^q Y_2 \Delta \ln FC_{t-i} + \sum_{i=1}^q Y_3 \Delta \ln MA_{t-i} + \sum_{i=1}^q Y_4 \Delta \ln AT_{t-i} \\ & + \sum_{i=1}^q Y_5 \Delta \ln AR_{t-i} + \sum_{i=1}^q Y_6 \Delta \ln CO_{2t-i} + \sum_{i=1}^q Y_7 \Delta \ln MP_{t-i} + \beta_1 \ln CR_{t-1} + \beta_2 \ln FC_{t-1} \\ & + \beta_3 \ln MA_{t-1} + \beta_4 \ln AT_{t-1} + \beta_5 \ln AR_{t-1} + \beta_6 \ln CO_{2t-1} + \beta_7 \ln MP_{t-1} + \varepsilon_t \quad (9) \end{aligned}$$

where all the study variables are well-defined as previously, Δ means the operator of the first difference, ε_t indicates the error term, Y refers to the SR dynamics, and β represents the LR coefficients. The ARDL method estimates the LR association between the considered variables in the model with the help of the Wald test to check the null hypothesis.

$H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = 0$ against the alternative hypothesis; $H_0 : \beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq \beta_6 \neq \beta_7 \neq 0$. The computed F-stat derived from the Wald test is compared with the critical values specified by Pesaran et al. (2001). The critical values of F-stat have two bounds, for example, Upper Critical Bound (UCB; $I(0)$) and Lower Critical Bound (LCB; $I(1)$). If the calculated F-stat is $>$ the UCB hypothesis relating to, no long-term cointegration will be rejected. If the calculated F-stat lies between UCB and LCB, inconclusive outcomes occur. Once the LR association is proven among the variables, the ARDL framework and ECM are used to estimate the Short-term (ST) and Long-term (LT) coefficients based on the following equations:

$$\begin{aligned} \Delta \ln MP_t = & Y_0 + \sum_{i=1}^p Y_1 \Delta \ln MP_{t-i} + \sum_{i=1}^q Y_2 \Delta \ln CO_{2t-i} + \sum_{i=1}^q Y_3 \Delta \ln AR_{t-i} + \sum_{i=1}^q Y_4 \Delta \ln AT_{t-i} \\ & + \sum_{i=1}^q Y_5 \Delta \ln MA_{t-i} + \sum_{i=1}^q Y_6 \Delta \ln FC_{t-i} + \sum_{i=1}^q Y_7 \Delta \ln CR_{t-i} + \Omega_1 ECT_{t-1} + \varepsilon_t \quad (10) \end{aligned}$$

$$\begin{aligned} \Delta \ln CO_{2t} = & Y_0 + \sum_{i=1}^p Y_1 \Delta \ln CO_{2t-i} + \sum_{i=1}^q Y_2 \Delta \ln MP_{t-i} + \sum_{i=1}^q Y_3 \Delta \ln AR_{t-i} + \sum_{i=1}^q Y_4 \Delta \ln AT_{t-i} \\ & + \sum_{i=1}^q Y_5 \Delta \ln MA_{t-i} + \sum_{i=1}^q Y_6 \Delta \ln FC_{t-i} + \sum_{i=1}^q Y_7 \Delta \ln CR_{t-i} + \Omega_2 ECT_{t-1} + \varepsilon_t \end{aligned} \quad (11)$$

$$\begin{aligned} \Delta \ln AR_t = & Y_0 + \sum_{i=1}^p Y_1 \Delta \ln AR_{t-i} + \sum_{i=1}^q Y_2 \Delta \ln CO_{2t-i} + \sum_{i=1}^q Y_3 \Delta \ln MP_{t-i} + \sum_{i=1}^q Y_4 \Delta \ln AT_{t-i} \\ & + \sum_{i=1}^q Y_5 \Delta \ln MA_{t-i} + \sum_{i=1}^q Y_6 \Delta \ln FC_{t-i} + \sum_{i=1}^q Y_7 \Delta \ln CR_{t-i} + \Omega_3 ECT_{t-1} + \varepsilon_t \end{aligned} \quad (12)$$

$$\begin{aligned} \Delta \ln AT_t = & Y_0 + \sum_{i=1}^p Y_1 \Delta \ln AT_{t-i} + \sum_{i=1}^q Y_2 \Delta \ln AR_{t-i} + \sum_{i=1}^q Y_3 \Delta \ln CO_{2t-i} + \sum_{i=1}^q Y_4 \Delta \ln MP_{t-i} \\ & + \sum_{i=1}^q Y_5 \Delta \ln MA_{t-i} + \sum_{i=1}^q Y_6 \Delta \ln FC_{t-i} + \sum_{i=1}^q Y_7 \Delta \ln CR_{t-i} + \Omega_4 ECT_{t-1} + \varepsilon_t \end{aligned} \quad (13)$$

$$\begin{aligned} \Delta \ln MA_t = & Y_0 + \sum_{i=1}^p Y_1 \Delta \ln MA_{t-i} + \sum_{i=1}^q Y_2 \Delta \ln AT_{t-i} + \sum_{i=1}^q Y_3 \Delta \ln AR_{t-i} + \sum_{i=1}^q Y_4 \Delta \ln CO_{2t-i} \\ & + \sum_{i=1}^q Y_5 \Delta \ln MP_{t-i} + \sum_{i=1}^q Y_6 \Delta \ln FC_{t-i} + \sum_{i=1}^q Y_7 \Delta \ln CR_{t-i} + \Omega_5 ECT_{t-1} + \varepsilon_t \end{aligned} \quad (14)$$

$$\begin{aligned} \Delta \ln FC_t = & Y_0 + \sum_{i=1}^p Y_1 \Delta \ln FC_{t-i} + \sum_{i=1}^q Y_2 \Delta \ln MA_{t-i} + \sum_{i=1}^q Y_3 \Delta \ln AT_{t-i} + \sum_{i=1}^q Y_4 \Delta \ln AR_{t-i} \\ & + \sum_{i=1}^q Y_5 \Delta \ln CO_{2t-i} + \sum_{i=1}^q Y_6 \Delta \ln MP_{t-i} + \sum_{i=1}^q Y_7 \Delta \ln CR_{t-i} + \Omega_6 ECT_{t-1} + \varepsilon_t \end{aligned} \quad (15)$$

$$\begin{aligned} \Delta \ln CR_t = & Y_0 + \sum_{i=1}^p Y_1 \Delta \ln CR_{t-i} + \sum_{i=1}^q Y_2 \Delta \ln FC_{t-i} + \sum_{i=1}^q Y_3 \Delta \ln MA_{t-i} + \sum_{i=1}^q Y_4 \Delta \ln AT_{t-i} \\ & + \sum_{i=1}^q Y_5 \Delta \ln AR_{t-i} + \sum_{i=1}^q Y_6 \Delta \ln CO_{2t-i} + \sum_{i=1}^q Y_7 \Delta \ln MP_{t-i} + \Omega_7 ECT_{t-1} + \varepsilon_t \end{aligned} \quad (16)$$

where ECM_{t-1} denotes the error correction term, which measures the speed of adjustment to the LR. This investigation used several tests for diagnoses, including heteroscedasticity, serial correlation, normality, and the Ramsey-RESET test, to check the model's fitness. Also, the stability of the ARDL model is verified by applying both the Cumulative sum (CUSUM) and Cumulative sum of squares (CUSUMSQ) tests proposed by Brown et al. (1975).

Table 2 Results of the standard unit root tests

Variables	ADF				P-P			
	@Level		@First Diff		@Level		@First Diff	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept	Intercept	Trend and Intercept
LnMP	0.495	0.055**	–	–	0.307	0.107	0.000***	0.000***
LnCO ₂	0.777	0.510	0.000***	0.000***	0.813	0.233	0.000***	0.000***
LnAR	0.019**	0.033**	–	–	0.000***	0.000***	–	–
LnAT	0.027**	0.003***	–	–	0.028**	0.003***	–	–
LnMA	0.001***	0.002***	–	–	0.000***	0.000***	–	–
LnFC	0.469	0.801	0.000***	0.000***	0.391	0.735	0.000***	0.000***
LnCR	0.913	0.070*	–	–	0.905	0.426	0.001***	0.006***

***Reveals 1% level of significance, ** Reveals 5% level of significance, and * Reveals 10% level of significance

Table 3 Results of ARDL cointegrating

Estimated models	F-statistic	Cointegration exist
F_{LnMP} (LnMP/LnCO ₂ , LnAR, LnAT, LnMA, LnFC, LnCR)	6.087***	Yes
F_{LnCO_2} (LnCO ₂ /LnMP, LnAR, LnAT, LnMA, LnFC, LnCR)	4.210**	Yes
F_{LnAR} (LnAR/LnCO ₂ , LnMP, LnAT, LnMA, LnFC, LnCR)	3.938*	Yes
F_{LnAT} (LnAT/LnAR, LnCO ₂ , LnMP, LnMA, LnFC, LnCR)	6.024***	Yes
F_{LnMA} (LnMA/LnAT, LnAP, LnCO ₂ , LnMP, LnFC, LnCR)	4.026**	Yes
F_{LnFC} (LnFC/LnMA, LnAT, LnAP, LnCO ₂ , LnMP, LnCR)	3.911*	Yes
F_{LnCR} (LnCR/LnFC, LnMA, LnAT, LnAP, LnCO ₂ , LnMP)	5.752***	Yes
Significance	$I(0)$	$I(1)$
10%	2.53	3.59
5%	2.87	4.00
1%	3.6	4.90

***Reveals significant at 1% level, ** Reveals significant at 5% level, and * Reveals significant at 10% level

4 Empirical results and discussions

4.1 Stationary of the time-series data

The ARDL procedure is more appropriate when all the considered variables are stationary/integrated at the $I(0)$ or at the $I(1)$; however, it does not work for the $I(2)$ series (Damane & Sekantsi, 2018; Nkoro & Uko, 2016; Obeng & Sakyi, 2017). Several studies used multiple types of unit root tests, including the DF-GLS test advanced by Elliott et al. (1992), the P-P test proposed by Phillips and Perron (1988), and the ADF test developed by Dickey and Fuller (1979). The present study utilized the P-P and ADF tests. The estimated results of both tests are reported in Table 2. The ADF test results show that maize production,

Table 4 LR results based on the ARDL (1, 2, 2, 0, 2, 0, 1) model

Variables	Coefficient	Std. Error	t-Statistic	Prob
LnCO ₂	- 0.141***	0.040	- 3.538	(0.002)
LnAR	0.106	0.084	1.261	(0.225)
LnAT	- 0.455*	0.244	- 1.862	(0.081)
LnMA	1.787***	0.373	4.785	(0.000)
LnFC	0.024**	0.008	2.846	(0.011)
LnCR	- 0.150	0.088	- 1.702	(0.108)
Constant	- 8.772	5.090	- 1.723	(0.104)
@Trend	0.036***	0.005	7.071	(0.000)

***Reveals 1% level of significance, ** Reveals 5% level of significance, and * Reveals 10% level of significance

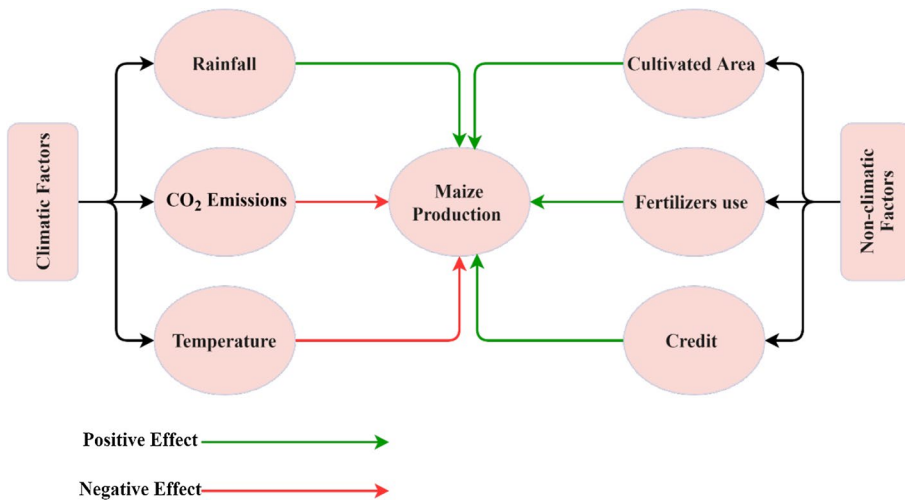


Fig. 8 Summary of Long-run (LR) estimate

rainfall, temperature, maize area, and credit are stationary in levels $I(0)$. At the same time, CO₂ emissions and fertilizers use are stationary after the first difference $I(1)$. As none of the undertaken variables are integrated at the $I(2)$, the study proceeds with the ARDL bounds method to cointegration to discover the long-term (LT) connection among variables.

4.2 Bounds test results for long-term (LT) cointegration

As none of the variables is integrated at the $I(2)$, the study explores the LT association among the variables using the ARDL bounds testing approach. Table 3 presents the results, indicating the F-stat value (6.087***) of the model F_{LnMP} ($LnMP/LnCO_2, LnAR, LnAT, LnMA, LnFC, LnCR$) is above the values of UCB. It implies that the LT cointegration is present amid the variables. Similarly, the calculated F-stat (4.210**) for the model F_{LnCO_2} ($LnCO_2/LnMP, LnAR, LnAT, LnMA, LnFC, LnCR$) is also above the mentioned value which proves the existence of the LT association between variables.

Furthermore, the respective computed F-stat (3.938*, 6.024***, 4.026**, 3.911*, and 5.752***) of the models F_{LnAR} ($LnAR/LnCO_2$, $LnMP$, $LnAT$, $LnMA$, $LnFC$, $LnCR$), F_{LnAT} ($LnAT/LnAR$, $LnCO_2$, $LnMP$, $LnMA$, $LnFC$, $LnCR$), F_{LnMA} ($LnMA/LnAT$, $LnAP$, $LnCO_2$, $LnMP$, $LnFC$, $LnCR$), F_{LnFC} ($LnFC/LnMA$, $LnAT$, $LnAP$, $LnCO_2$, $LnMP$, $LnCR$), and F_{LnCR} ($LnCR/LnFC$, $LnMA$, $LnAT$, $LnAP$, $LnCO_2$, $LnMP$) are above than the values of UCB at 10, 5, and 1% significant levels. The conclusions verify the presence of the LT steady relationships among the variables.

4.3 Long-run (LR) estimation

As the LT relationship is established amid all the variables, the next step of the study is to examine the LR and SR impacts of climatic factors, including CO₂ emissions, rainfall, and temperature on maize production with the incorporation of maize area, fertilizers use, and credit as essential determinants of maize production using the ARDL method. The LR and SR findings are given in Table 4, and Fig. 8 displays the summary of the LR estimate.

Estimating the climatic factors reveals the highly significant and negative influence (− 0.141) of carbon dioxide emissions on maize production in the LR. It implies that an increase of 1% in atmospheric carbon dioxide emissions will hamper the LR maize yield by 0.141%. These results are similar to the studies of Ahmad et al. (2020), Chandio et al. (2021b), and Warsame et al. (2021). For instance, the empirical findings by Chandio et al. (2020b) report that agricultural production is negatively affected by CC in the LR. Next, the rainfall (precipitation) result is not significant in the LR. Yet, it contributes positively (0.106) to maize production, which implies that a surge of 1% in precipitation will improve the LR maize production by 0.106%. These findings are in-line with the outcomes reported by Ammani et al. (2012) and Khan et al. (2019), where the latter reported that the precipitation significantly improved maize production in Pakistan. The estimation also provided the significantly negative LR coefficient (0.455) of temperature, implying that a 1% increase in temperature negatively affects maize production in the LR—decreasing its production by 0.455%. We also find our results similar to the outcomes of Picson et al. (2020) and Khan et al. (2019), who collectively revealed the significantly negative impact of temperature in the LR. Likewise, Abbas (2021) examined the impacts of climate change on crops production; findings revealed that annual temperature has a negative long-run impact on crops production.

Therefore, based on the reported results, the researchers conclude the significantly negative impact of CC and temperature and the positive yet insignificant impact of rainfall on maize production. To this end, if current varieties are grown, the CC would decrease maize yield by an average of 3–8% and 5–14% in 2030 and 2050, respectively (Tesfaye et al., 2017). With a high level of climate warming, substantial yield reductions are projected in lower latitudes, particularly for main food crops such as maize and wheat (Porter et al., 2014).

Following the results of climatic factors, the evidence from non-climatic factors reveals that maize area (1.787) and fertilizers use (0.024) positively and significantly influence maize production in the LR. It implies that increasing 1% in maize area and increasing fertilizers will increase LR maize production by 1.787% and 0.024%, respectively. These results align with Ammani et al. (2012), who reported that input factors, including area cultivated and chemical fertilizers usage, positively impact maize production in Nigeria. Further, adopting modern technologies such as improved seeds, fertilizers use, pesticides, and advanced farming methods, significantly improve per worker agricultural productivity.

Table 5 SR results based on the ARDL (1, 2, 2, 0, 2, 0, 1) model

Variables	Coefficient	Std. Error	t-Statistic	Prob
$\Delta \text{LnMP}(-1)$	0.347	0.200	1.730	(0.102)
ΔLnCO_2	-0.050	0.032	-1.557	(0.138)
$\Delta \text{LnCO}_2(-1)$	0.007	0.034	0.231	(0.820)
$\Delta \text{LnCO}_2(-2)$	-0.050*	0.025	-1.984	(0.064)
ΔLnAR	-0.003	0.028	-0.108	(0.915)
$\Delta \text{LnAR}(-1)$	0.120***	0.024	5.006	(0.000)
$\Delta \text{LnAR}(-2)$	-0.048*	0.026	-1.842	(0.084)
ΔLnAT	-0.297*	0.156	-1.893	(0.076)
ΔLnMA	1.553***	0.267	5.799	(0.000)
$\Delta \text{LnMA}(-1)$	0.333	0.371	0.897	(0.382)
$\Delta \text{LnMA}(-2)$	-0.720***	0.162	-4.426	(0.000)
ΔLnFC	0.016**	0.006	2.442	(0.026)
ΔLnCR	0.014	0.043	0.327	(0.747)
$\Delta \text{LnCR}(-1)$	-0.112**	0.052	-2.154	(0.046)
Constant	-5.726**	1.989	-2.878	(0.010)
@Trend	0.023***	0.006	3.493	(0.003)
CointEq (-1)	-0.652***	0.200	-3.252	(0.005)
Diagnostic tests				
Values	Test stat		Prob	
R-squared	0.997		-	
Adjusted R^2	0.994		-	
F-statistic	74.621***		(0.000)	
Normality test	0.003		(0.998)	
Breusch–Godfrey-LM test	2.367		(0.210)	
BPG heteroscedasticity test	1.252		(0.329)	
Ramsey-RESET test	0.072		(0.943)	

***Reveals significant at 1% level, **Reveals significant at 5% level, and *Reveals significant at 10% level

Contrary to these two factors, the coefficient for the credit appeared to be negative yet statistically insignificant in the LR, which implies that a 1% decrease in credit supply will increase LR maize production by 0.150%. Our findings are contrary to the outcomes of Kumar et al. (2020) and Rehman et al. (2019), where the latter revealed the positive long-run impact of credit distribution, fertilizer usage, and improved seeds on the agricultural sector value-added for Pakistan. Therefore, the researchers conclude that the impact of credit supply cannot be determined due to the insignificant results, and it needs further investigation.

4.4 Short-run (SR) dynamics

The study utilized the ECM-ARDL framework to examine SR dynamics of the association between climatic and non-climatic factors and maize production in Nepal. The estimated SR coefficients composed of the associated diagnostic test findings are provided in Table 5.

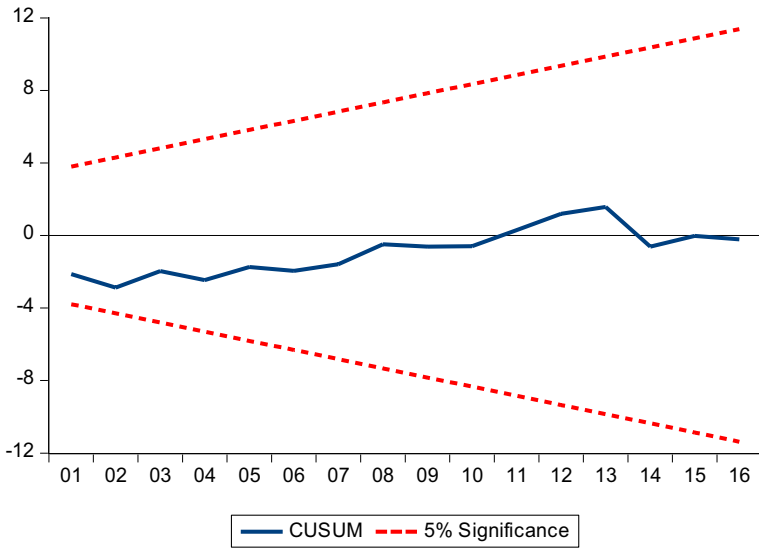


Fig. 9 CUSUM test

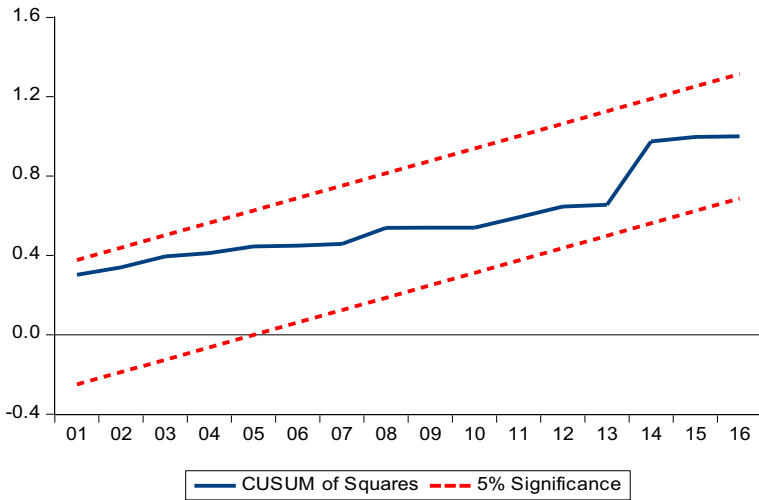


Fig. 10 CUSUM of Squares test

The negative and highly significant lagged ECT estimated coefficient indicates the speed of adjustment to the LR following a shock in the previous period. The value of ECT is 65%,

which implies that any upset in the previous period adjusts back to equilibrium in the LR at the speed of 65%.

The SR estimations for the climatic factors such as CO₂ emissions and temperature negatively influenced maize production, whereas the lagged precipitation positively contributed to maize production. These results are parallel to the results reported in the LR. Furthermore, results show that non-climatic factors, including maize area and fertilizers use, significantly increase maize production in the SR, as reported in the LR results. Nevertheless, credit supply turned positive yet insignificant in the SR. The results are in-line with the findings reported by Chandio et al. (2020a), Das and Hossain (2019), and Ozdemir (2021). For instance, in the case of China, Chandio et al. (2020a) examined the effect of financial development on agricultural production by undertaking the data of 1989–2016. The expected results showed that financial development has positive and significant long- and short-run impacts on agricultural production. Similarly, in the context of Bangladesh, Das and Hossain (2019) explored the impact of credit and fertilizers (chemical) on paddy production by undertaking the data of 1995–2016. Findings provided the significant positive impact of credit on paddy production, whereas the impact of fertilizers is found to be positive but not significant. Lastly, Ozdemir (2021) reported that fertilizers consumption positively contributed to agricultural production in both periods, including long-run and short-run in selected Asian countries.

The study also employed various diagnostic tests like normality, heteroscedasticity, serial correlation, and Ramsey-RESET. These tests confirmed that the estimated model residuals are normally distributed in the LR, free from all issues, and well-established. Respective results are reported in Table 5. Similarly, both CUSUM and CUSUMSQ tests also ensure that the model is robust and stable. Figures 9 and 10 provide the depiction of the reported tests.

4.5 VECM, IRF, and VDM results

The long-run (LR) connection reported in Table 4 indicated the (at least) unidirectional causality among described variables. To this end, the study employed the VECM causality test, and the respected results are provided in Table 6. The primary maize production model indicated that rainfall and maize area have two-way causal associations with maize production, whereas the CO₂ emissions and credit have unidirectional causality with maize production.

The primary model outcomes also advocated that these variables have a close connection with maize production; especially CO₂ emissions and rain significantly affect maize production, among other climatic factors. Further, a one-way connection runs from CO₂ emissions to maize production, rainfall, temperature, and cultivation area, respectively. The connection running from CO₂ emissions, temperature, and credit toward rainfall is unidirectional. However, rainfall and maize production have bidirectional causality. Similarly, the temperature is linked with CO₂ emissions and credit. The connection between cultivation area and maize production is bidirectional, and the one-way causality link is significant from CO₂ emissions and credit to cultivation area. Finally, fertilizers and credit also have a significant connection. To summarize, all of the study outcomes suggested that the link among all variables is significant; also, most of the directions justified the ARDL model findings in the SR. The LR term of all models shows a significant association of all variables in the LR for Nepal.

Table 6 VECM-based ganger causality estimates

Dependent variable	Independent variables							
	ΔLnMP	ΔLnCO_2	ΔLnAR	ΔLnAT	ΔLnMA	ΔLnFC	ΔLnCR	ECM_{t-1}
ΔLnMP	–	10.778*** (0.004)	5.139* (0.076)	0.112 (0.945)	8.065** (0.017)	0.662 (0.718)	5.766** (0.055)	– 0.030 (– 0.213)
ΔLnCO_2	3.115 (0.2106)	–	1.091 (0.579)	0.082 (0.959)	0.601 (0.740)	2.800 (0.246)	7.810** (0.020)	– 0.440*** (– 3.832)
ΔLnAR	10.110*** (0.0064)	10.970*** (0.004)	–	5.321* (0.069)	0.625 (0.731)	0.140 (0.932)	7.617** (0.022)	– 0.333* (– 1.706)
ΔLnAT	0.301 (0.8601)	11.899*** (0.002)	0.520 (0.770)	–	0.091 (0.955)	2.282 (0.319)	7.685** (0.021)	– 1.243*** (– 4.598)
ΔLnMA	11.426*** (0.0033)	6.516** (0.038)	3.066 (0.215)	1.273 (0.529)	–	1.185 (0.552)	5.959** (0.050)	– 0.011 (– 0.303)
ΔLnFC	0.233 (0.889)	4.352 (0.1143)	5.285* (0.071)	0.199 (0.905)	0.154 (0.925)	–	14.492*** (0.000)	– 0.041 (– 0.389)
ΔLnCR	0.682 (0.710)	3.560 (0.168)	1.980 (0.371)	5.441* (0.065)	0.892 (0.639)	5.084* (0.078)	–	– 0.038 (– 0.957)

***Reveals 1% level of significance, **Reveals 5% level of significance, *Reveals 10% level of significance

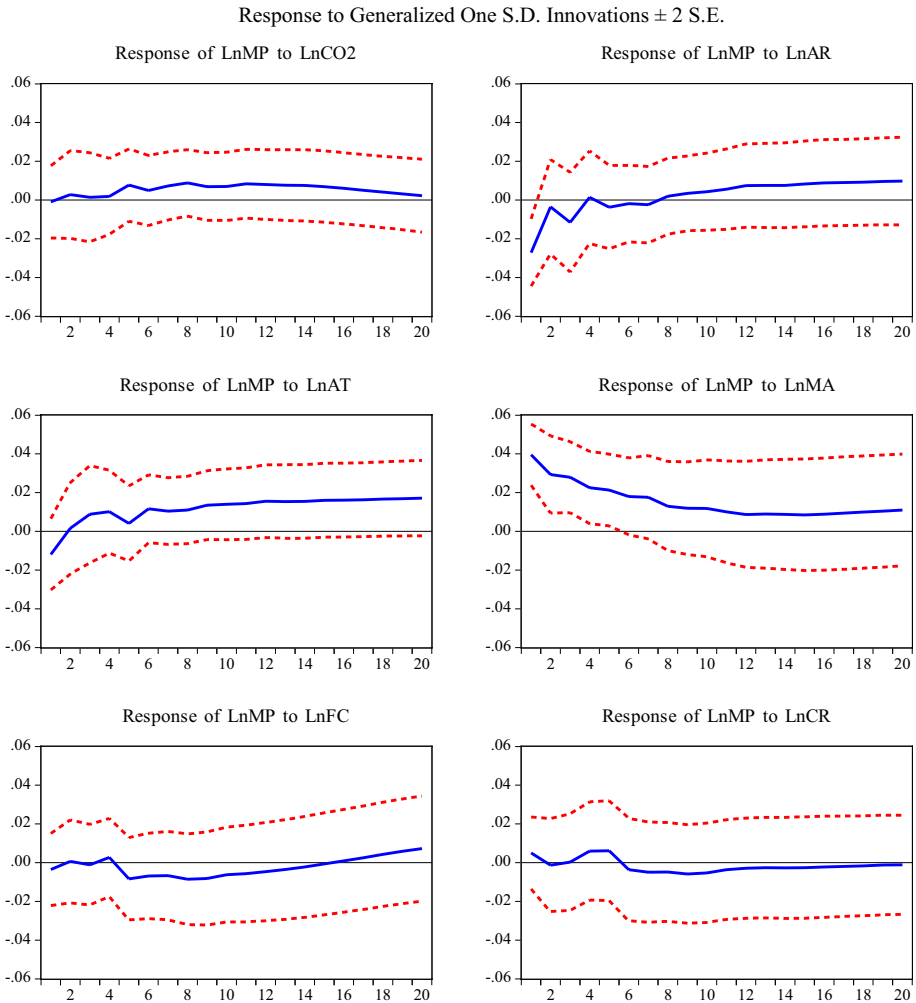


Fig. 11 Impulse response function

The study also utilized the IRF to test the feedback of the study variables. The results, displayed in Fig. 11, clearly show that all variables significantly respond to maize production. Both rainfall and CO₂ emissions are gradually increasing as production increases, and a similar turn can be observed in temperature and cultivation area. Likewise, the fertilizers and credit slowly yet gradually enhance the productivity of maize. The IRF results also suggest that the association of all factors toward maize production is strong and effective in the long-run.

Since time limitation is a restriction in causal analysis, this study applied the generalized forecast error VDM to examine the consistency and verify the inevitability of the causal associations between undertaken predictors and predictands. The VDM test results are presented in Table 7. It reports that the decomposition of maize production exposes that 78.84% quantity of maize value is described by its innovative shocks. Also, the contribution of CO₂ and cultivation area increases the maize production; however, the share of

Table 7 Results of variance decomposition

Variance decomposition of LnMP								
Period	SE	LnMP	LnCO ₂	LnAR	LnAT	LnMA	LnFC	LnCR
1	0.052	100.000	0.000	0.000	0.000	0.000	0.000	0.000
2	0.096	78.849	7.821	4.304	1.4584	7.520	0.012	0.033
3	0.127	77.978	7.718	3.445	3.549	6.966	0.207	0.133
4	0.161	75.418	7.596	2.524	3.329	10.796	0.129	0.205
5	0.193	69.630	8.331	4.264	3.911	12.569	0.928	0.363
6	0.220	68.895	7.461	4.315	4.324	13.009	1.643	0.350
7	0.252	67.872	7.530	4.044	4.107	14.456	1.529	0.458
8	0.278	67.710	7.475	3.693	4.083	14.506	2.095	0.434
9	0.307	67.581	7.122	4.117	3.999	14.711	2.045	0.421
10	0.335	68.413	6.912	3.835	3.741	14.467	2.205	0.424

cultivation area is higher than CO₂ emissions. Additionally, innovative shocks to rainfall, temperature, and fertilizers increase slowly. The average share of credit toward maize production is low compared to all other factors, yet the trend is still upward. Generally, the VDM also confirms that the impact of these factors is increasing over time, and intensity varies among these factors. Therefore, the researchers conclude that the impact of climatic and non-climatic factors is consistent on maize production in Nepal.

5 Conclusions, policy implications, and future research agenda

The present study examined the long-run (LR) and short-run (SR) impacts of climatic factors (i.e., CO₂ emissions, rainfall, and temperature) and non-climatic factors (i.e., maize area, fertilizers use, and credit supply) on maize production in Nepal over the period ranging from 1983 to 2016. The ADF and P-P unit root tests confirmed the mixed order of integration among variables, and the computed ARDL-bounds F-statistics showed strong evidence of the LT relationship between variables. The empirical findings revealed that climatic factors such as CO₂ emissions and temperature negatively influenced maize production in the LR and SR. In contrast, the effect of rainfall remained positive in both periods. The study also considered the non-climatic factors like maize area and fertilizers use, which positively enhanced maize production in the LR and SR. In contrast, the credit supply estimation remained inconclusive as it remained positive in SR and became negative in the LR.

Additionally, VECM causality results reveal that precipitation and maize area have two-way causal associations with maize production, whereas the CO₂ emissions and credit represent unidirectional causality with maize production. These results advocate the presence of a close connection between predictors and maize production; especially CO₂ emissions and precipitation significantly affected maize production, among other climatic factors in SR and LR. Furthermore, the VDM outcomes suggested that the contribution of CO₂ and cultivation area rises steadily to maize production; however, the share of cultivation area is higher than CO₂ emissions. Thus, the impact of non-climatic and climatic factors is

consistent on maize production in Nepal under these robustness check analyses for LR and SR. Finally, the robust findings can be generalized to other countries with similar environmental conditions because of robustness.

5.1 Theoretical/Methodological and policy implications

The present paper provides theoretical/methodological implications in three levels. Initially, the findings confirm the underlying assumption, i.e., climate change negatively impacts agricultural production, and production-related variables positively impact agricultural production. The results can also be applied to the other crops and the countries with similar environmental conditions. Next, the paper adds to the available literature on the impacts of environmental factors on maize (cereals) production, which is an integral part of food security and the UN's Agenda 2030 for sustainable development goals (FAO, 2021; Langner et al., 2019). Lastly, to get more reliable outcomes, this study implies the most robust econometric approaches, such as the ARDL, VECM, Granger causality, IRF, and VDM. The robust findings of this paper also endorse the use of stated econometric methods to measure similar phenomena across other crops, countries, and years.

Based on the study findings, the responsible institutions (governments) can form applicable policies for better maize production. For instance, better environmental quality must be the key to increasing production; therefore, the governments should cut down the carbon footprints (per capita carbon production as well) to maintain the lower temperature nationwide. Resultantly, it will increase the rainfall and enhance overall productivity. On the other hand, governments should encourage renewable energy usage and support organic farming to decrease total CO₂ emissions and maintain a favorable temperature. To this end, stats reported by IRENA-International Renewable Energy Agency (2020) reported that only renewables and energy efficiency electrification could reduce the over 90% energy-associated carbon footprint. Likewise, Horrillo et al. (2020) and Clark (2020) also conclude that organic farming can be a strategy to reduce carbon emissions.

Next, since the study provided encouraging results of fertilizers consumption, the strategies should be formed to increase the utilization of agricultural waste as organic fertilizers. It will increase the land fertility as well as cut the carbon emission resulting from agricultural waste burning. Lastly, concerning the credit supply to the agricultural sector, despite its inconclusive results, the study suggests that the government can introduce various support schemes to raise the small farmers' income and provide them sufficient financial backup for modern technology use for a better environment and production in the long-run (Nakano & Magezi, 2020).

Following the proposed policies, the governments can also develop the framework to meet the agenda 2030 on food security (SDG 02: Zero Hunger) as maize constitutes a substantial chunk of the total global cereal production (FAO, 2021) and a significant proportion of the population relies on this for nutrition (Nuss & Tanumihardjo, 2010). Presently, it is cultivated in 170 countries over 185 million ha with a productivity of 5.62 t/ha (FAOSTAT, 2019); however, due to the sharp cut in maize production, food security (SDG 02) is at stake, which questions the lives of billions of people (FAO, 2021). Therefore, governments, mainly developing countries, can also focus on introducing and marketing "*maize as a cereal*" policy to feed their population and meet the Agenda 2030 – Sustainable Development Goals.

5.2 Future research agenda

The study provides essential future research directions based on the long-run (LR) and short-run (SR) results. *Firstly*, the researchers may organize the impact evaluation studies to investigate the impact of current and proposed policies on maize production. The findings will strengthen the practical implications of the research and consequent guidelines for policymakers. *Secondly*, the researchers may also develop the panel of developing countries and determine the impact of environmental factors and the role played by production-related variables in coping with the effects.

Thirdly, the developing countries are at stake due to intensified climatic impacts on agriculture. To this end, Elliott (2015) pointed out that the trade can bring food security to the 800 million people in the world. Therefore, future studies can also introduce mutual trade among countries to investigate their impact on food security. Additionally, the researchers can compare the panel of developing, MENA, GCC, and developed countries. The findings will provide in-depth results on the group-wise impact of environmental factors as developing, mainly MENA countries, face the significant effect of CC (Waha et al., 2017). *Finally*, future researchers can also investigate the difference between crop productivity from organic and synthetic fertilizers, mainly in cereal crops, due to their importance in food security. The findings will further benchmark fertilizers use for enhancing agricultural productivity to meet the Agenda 2030–SDG.

References

- Abbas, S. (2020). Climate change and cotton production: An empirical investigation of Pakistan. *Environmental Science and Pollution Research*, 27, 29580–29588.
- Abbas, S. (2021). Climate change and major crop production: Evidence from Pakistan. *Environmental Science and Pollution Research*, 1–9.
- Agovino, M., Casaccia, M., Ciommi, M., Ferrara, M., & Marchesano, K. (2019). Agriculture, climate change and sustainability: The case of EU-28. *Ecological Indicators*, 105, 525–543.
- Ahmad, S., Tariq, M., Hussain, T., Abbas, Q., Elham, H., Haider, I., & Li, X. (2020). Does Chinese FDI, Climate Change, and CO₂ Emissions Stimulate Agricultural Productivity? *An Empirical Evidence from Pakistan. Sustainability*, 12(18), 7485.
- Ahsan, F., Chandio, A. A., & Fang, W. (2020). Climate change impacts on cereal crops production in Pakistan. *International Journal of Climate Change Strategies and Management*, 12, 257–269.
- Ali, E. (2021). Farm Households' Adoption of Climate-smart Practices in Subsistence Agriculture: Evidence from Northern Togo. *Environmental Management*, 67(5), 949–962.
- Ali, A., & Erenstein, O. (2017). Assessing farmer use of climate change adaptation practices and impacts on food security and poverty in Pakistan. *Climate Risk Management*, 16, 183–194.
- Ali, S., Liu, Y., Nazir, A., Ishaq, M., & Shah, T. (2020). DOES TECHNICAL PROGRESS MITIGATE CLIMATE EFFECT ON CROPS YIELD IN PAKISTAN? *Journal of Animal and Plant Sciences*, 30(3), 663–676.
- Ammani, A., & Ja'afaru, A., Aliyu, J., Arab, A. (2012). Climate change and maize production: Empirical evidence from Kaduna State. *Nigeria. Journal of Agricultural Extension*, 16(1), 1–8.
- Aryal, J. P., Sapkota, T. B., Khurana, R., Khatri-Chhetri, A., & Jat, M. L. (2019). Climate change and agriculture in South Asia: adaptation options in smallholder production systems. *Environment, Development and Sustainability*, 22, 5045–5075.
- Bandara, J. S., & Cai, Y. (2014). The impact of climate change on food crop productivity, food prices and food security in South Asia. *Economic Analysis and Policy*, 44(4), 451–465.
- Bank, W. 2019. World Bank (2018a): World development indicators. Available at <https://data.worldbank.org/indicator>.
- Benhin, J. K. (2006). *Climate change and South African agriculture: Impacts and adaptation options*. CEEPA discussion paper.


- Brizmohun, R. (2019). Impact of climate change on food security of small islands: The case of Mauritius, Natural Resources Forum. *Wiley Online Library*, 43, 154–163.
- Brown, R. L., Durbin, J., & Evans, J. M. (1975). Techniques for testing the constancy of regression relationships over time. *Journal of the Royal Statistical Society: Series B (methodological)*, 37(2), 149–163.
- Casemir, B. H., & Diaw, A. (2018). Analysis of Climate Change Effect on Agricultural Production in Benin. *Asian Journal of Agricultural Extension, Economics & Sociology*, 24, 1–12.
- Chandio, A. A., Magsi, H., & Ozturk, I. (2020). Examining the effects of climate change on rice production: Case study of Pakistan. *Environmental Science and Pollution Research*, 27(8), 7812–7822.
- Chandio, A. A., Jiang, Y., Rauf, A., Ahmad, F., Amin, W., & Shehzad, K. (2020b). Assessment of formal credit and climate change impact on agricultural production in Pakistan: A time series ARDL modeling approach. *Sustainability*, 12(13), 5241.
- Chandio, A. A., Jiang, Y., Abbas, Q., Amin, A., & Mohsin, M. (2020a). Does financial development enhance agricultural production in the long-run Evidence from China. *Journal of Public Affairs*. <https://doi.org/10.1002/pa.2342>
- Chandio, A. A., Jiang, Y., Ahmad, F., Adhikari, S., & Ain, Q. U. (2021a). Assessing the impacts of climatic and technological factors on rice production: Empirical evidence from Nepal. *Technology in Society*, 66, 101607.
- Chandio, A. A., Jiang, Y., Akram, W., Adeel, S., Irfan, M., & Jan, I. (2021b). Addressing the effect of climate change in the framework of financial and technological development on cereal production in Pakistan. *Journal of Cleaner Production*, 288, 125637.
- Chung, E.-S., & Kim, Y. (2014). Development of fuzzy multi-criteria approach to prioritize locations of treated wastewater use considering climate change scenarios. *Journal of Environmental Management*, 146, 505–516.
- Clark, S. (2020). Organic Farming and Climate Change: The Need for Innovation. *Sustainability*, 12(17), 7012.
- Damane, M., & Sekantsi, L. P. (2018). The sources of unemployment in Lesotho. *Modern Economy*, 9(5), 937–965.
- Das, M. R., & Hossain, M. A. (2019). Impact of agricultural loan disbursement and chemical fertilizer use on the rice production in Bangladesh. *Bangladesh Journal of Public Administration*, 27(2).
- Deressa, T. T., Hassan, R. M., & Ringler, C. (2011). Perception of and adaptation to climate change by farmers in the Nile basin of Ethiopia. *Journal of Agricultural Science*, 149(1), 23–31.
- Devkota, N., & Pajja, N. (2020). Impact of Climate Change on Paddy Production: Evidence from Nepal. *Asian Journal of Agriculture and Development*, 17, 63–78.
- Dewan, T., & H... (2015). Societal impacts and vulnerability to floods in Bangladesh and Nepal. *Weather & Climate Extremes*, 7, 36–42.
- Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74(366a), 427–431.
- Ding, Q., Chen, X., Hilborn, R., & Chen, Y. (2017). Vulnerability to impacts of climate change on marine fisheries and food security. *Marine Policy*, 83, 55–61.
- Elliott, K. A. (2015). *Food Security in Developing Countries: Is there a role for the WTO?* Center for Global Development.
- Elliott, G., Rothenberg, T. J., & Stock, J. H. (1992). Efficient Tests for an Autoregressive Unit Root. *Econometrica*, 64(4), 813–836.
- Engle, R. F., & Granger, C. W. (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica Journal of the Econometric Society*, 55, 251–276.
- FAO. (2021). FAO Cereal Supply and Demand Brief. World cereal inventories in 2021/22 expected to rise for the first time since 2017/18. Retrieved from FAO Cereal Supply and Demand Brief | World Food Situation | Food and Agriculture Organization of the United Nations. Accessed on August 30, 2021.
- FAOSTAT. (2019). *FAOSTAT database collections*. Rome.
- Fatuase, A., & Ajibefun, I. (2014). Perception and Adaptation to Climate Change among Farmers in Selected Communities of Ekiti State. *Nigeria. Gaziosmanpasa Niversitesi Ziraat Fakültesi Dergisi*, 31(3), 100–113.
- Ghimire, R., & Huang, W. C. (2015). Household wealth and adoption of improved maize varieties in Nepal: A double-hurdle approach. *Food Security*, 7(6), 1321–1335.
- Ghimire, R., & Huang, W.-C. (2016). Adoption pattern and welfare impact of agricultural technology: Empirical evidence from rice farmers in Nepal. *Journal of South Asian Development*, 11(1), 113–137.
- Ghimire, R., Wen-Chi, H., & Shrestha, R. B. (2015). Factors affecting adoption of improved rice varieties among rural farm households in Central Nepal. *Rice Science*, 22(1), 35–43.
- Gmann, H. (2015). How Much did Extreme Weather Events Impact Wheat Yields in Germany? - A Regionally Differentiated Analysis on the Farm Level. *Procedia Environmental Sciences*, 29, 119–120.

- Government of Nepal – GoN (2020). Statistical information on Nepalese agriculture 2076/77 (2019/20).
- Horrillo, A., Gaspar, P., & Escribano, M. (2020). Organic farming as a strategy to reduce carbon footprint in Dehesa agroecosystems: A case study comparing different livestock products. *Animals*, *10*(1), 162. <https://doi.org/10.3390/ani10010162>
- Im, E. S., Pal, J. S., & Eltahir, E. A. (2017). Deadly heat waves projected in the densely populated agricultural regions of South Asia. *Science Advances*, *3*(8), e1603322.
- International Renewable Energy Agency-IRENA (2020). How to transform the energy system and reduce carbon emissions. IRENA. Retrieved from <https://www.irena.org/DigitalArticles/2019/Apr/How-To-Transform-Energy-System-And-Reduce-Carbon-Emissions>. Accessed on December 11, 2021.
- Johansen, S., & Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration—with applications to the demand for money. *Oxford Bulletin of Economics and Statistics*, *52*(2), 169–210.
- Joshi, G. R., & Joshi, B. (2019). *Climate change impact on agricultural sector of Nepal: Implications for adaptation and resilience building. Agricultural Transformation in Nepal* (pp. 119–155). Springer.
- Karmakar, N., Chakraborty, A., & Nanjundiah, R. S. (2017). Increased sporadic extremes decrease the intra-seasonal variability in the Indian summer monsoon rainfall. *Scientific Reports*, *7*(1), 1–7.
- Khan, A., Ali, S., Shah, S. A., Khan, A., & Ullah, R. (2019). Impact of climate change on maize productivity in Khyber Pakhtunkhwa. *Pakistan. Sarhad Journal of Agriculture*, *35*(2), 594–601.
- Khanal, U., Wilson, C., Lee, B. L., & Hoang, V. N. (2018). Climate change adaptation strategies and food productivity in Nepal: A counterfactual analysis. *Climatic Change*, *148*(4), 575–590.
- Kogo, B. K., Kumar, L., & Koech, R. (2021). Climate change and variability in Kenya: A review of impacts on agriculture and food security. *Environment, Development and Sustainability*, *23*(1), 23–43.
- Kumar, A., Takeshima, H., Thapa, G., Adhikari, N., Saroj, S., Karkee, M., & Joshi, P. (2020). Adoption and diffusion of improved technologies and production practices in agriculture: Insights from a donor-led intervention in Nepal. *Land Use Policy*, *95*, 104621.
- Kumar, P., Sahu, N. C., Kumar, S., & Ansari, M. A. (2021). Impact of climate change on cereal production: evidence from lower-middle-income countries. *Environmental Science and Pollution Research*, 1–15.
- Kuttippurath, J., Murasingh, S., Stott, P. A., Sarojini, B. B., Jha, M. K., Kumar, P., & Pandey, P. C. (2021). Observed rainfall changes in the past century (1901–2019) over the wettest place on Earth. *Environmental Research Letters*, *16*(2), 024018.
- Langner, J. A., Zanon, A. J., Streck, N. A., Reiniger, L. R., Kaufmann, M. P., & Alves, A. F. (2019). Maize: Key agricultural crop in food security and sovereignty in a future with water scarcity. *Revista Brasileira De Engenharia Agrícola e Ambiental*, *23*, 648–654.
- Lu, S., Bai, X., Li, W., & Wang, N. (2019). Impacts of climate change on water resources and grain production. *Technological Forecasting and Social Change*, *143*, 76–84.
- MoAD. (2019). *Statistical information on Nepalese agriculture - Google scholar*. Ministry of Agriculture and Livestock Development.
- MoF. (2019). *Economic survey: Fiscal year 2018/19*. Ministry of Finance.
- Msowoya, K., Madani, K., Davtalah, R., Mirchi, A., & Lund, J. R. (2016). Climate Change Impacts on Maize Production in the Warm Heart of Africa. *Water Resources Management*, *30*, 5299–5312. <https://doi.org/10.1007/s11269-016-1487-3>
- Mulungu, K., Tembo, G., Bett, H., & Ngoma, H. (2021). Climate change and crop yields in Zambia: historical effects and future projections. *Environment, Development and Sustainability*, 1–22.
- Nakano, Y., & Magezi, E. F. (2020). The impact of microcredit on agricultural technology adoption and productivity: Evidence from randomized control trial in Tanzania. *World Development*, *133*, 104997. <https://doi.org/10.1016/j.worlddev.2020.104997>
- Nkoro, E., & Uko, A. K. (2016). Autoregressive Distributed Lag (ARDL) cointegration technique: Application and interpretation. *Journal of Statistical and Econometric Methods*, *5*(4), 63–91.
- NOAA National Centers for Environmental Information, State of the Climate: Global Climate Report for Annual 2020, online January 2021. Retrieved on March 15, 2021 from <https://www.ncdc.noaa.gov/sotc/global/202013>.
- NOAA National Centers for Environmental information, Climate at a Glance: Global Time Series, published December 2021, retrieved on December 18, 2021 from <https://www.ncdc.noaa.gov/cag/>
- Nuss, E. T., & Tanumihardjo, S. A. (2010). Maize: A paramount staple crop in the context of global nutrition. *Comprehensive Reviews in Food Science and Food Safety*, *9*(4), 417–436.
- Obeng, S. K., & Sakyi, D. (2017). Macroeconomic determinants of interest rate spreads in Ghana. *African Journal of Economic and Management Studies*, *8*, 76–88.
- Ozdemir, D. (2021). The Impact of Climate Change on Agricultural Productivity in Asian Countries: a heterogeneous panel data approach.
- Özdoğan, M. (2011). Modeling the impacts of climate change on wheat yields in Northwestern Turkey. *Agriculture, Ecosystems & Environment*, *141*(1–2), 1–12.

- Pathak, S. (2021). Determinants of flood adaptation: Parametric and semiparametric assessment. *Journal of Flood Risk Management*, 14(2), e12699.
- Parry, M., Parry, M. L., Canziani, O., Palutikof, J., Van der Linden, P., & Hanson, C. (2007). Climate change 2007-impacts, adaptation and vulnerability: Working group II contribution to the fourth assessment report of the IPCC. Cambridge University Press.
- Pender, J., Hazell, P. (2000). *Promoting sustainable development in less-favored areas*. International Food Policy Research Institute Washington, DC.
- Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16(3), 289–326.
- Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, 75(2), 335–346.
- Phukan, J., Pender, N. P., & Hardiman, O. (2007). Cognitive impairment in amyotrophic lateral sclerosis. *The Lancet Neurology*, 6(11), 994–1003.
- Pickson, R. B., & Boateng, E. (2021). Climate change: a friend or foe to food security in Africa? *Environment, Development and Sustainability*, 1–26.
- Pickson, R. B., He, G., & Boateng, E. (2021). Impacts of climate change on rice production: evidence from 30 Chinese provinces. *Environment, Development and Sustainability*, 1–19.
- Pickson, R. B., He, G., Ntiamoah, E. B., & Li, C. (2020). Cereal production in the presence of climate change in China. *Environmental Science and Pollution Research*, 1–12.
- Porter, J. R., Xie, L., Challinor, A. J., Cochrane, K., Howden, S. M., Iqbal, M. M., Lobell, D. B., Travasso, M. I. (2014). Food security and food production systems. In *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA. http://ipcc-wg2.gov/AR5/images/uploads/WGIIAR5-Chap7_FGDall.pdf.
- Potgieter, A., Meinke, H., Doherty, A., Sadras, V. O., Hammer, G., & Crimp..., S. (2013). Spatial impact of projected changes in rainfall and temperature on wheat yields in Australia. *Climatic Change*, 117(1–2), 163–179.
- Rakshit, S., Hariprasanna, K., Gomashe, S., Ganapathy, K., Das, I., Ramana, O., Dhandapani, A., & Patil, J. (2014). Changes in Area, Yield Gains, and Yield Stability of Sorghum in Major Sorghum-Producing Countries, 1970 to 2009. *Crop Science*, 54(4), 1571–1584.
- Rayamajhee, V., & Bohara, A. K. (2019). Do voluntary associations reduce hunger? An empirical exploration of the social capital-food security nexus among food impoverished households in western Nepal. *Food Security*, 11(2), 405–415.
- Rayamajhee, V., Guo, W., & Bohara, A. K. (2020). The Impact of Climate Change on Rice Production in Nepal. *Economics of Disasters and Climate Change*, 5, 111–134.
- Rayamajhee, V., Guo, W., & Bohara, A. K. (2021). The impact of climate change on rice production in Nepal. *Economics of Disasters and Climate Change*, 5(1), 111–134.
- Raymundo, R., Asseng, S., Robertson, R., Petsakos, A., Hoogenboom, G., Quiroz, R., Hareau, G., & Wolf, J. (2018). Climate change impact on global potato production. *European Journal of Agronomy*, 100, 87–98.
- Rehman, A., Chandio, A. A., Hussain, I., & Jingdong, L. (2019). Fertilizer consumption, water availability and credit distribution: Major factors affecting agricultural productivity in Pakistan. *Journal of the Saudi Society of Agricultural Sciences*, 18(3), 269–274.
- Rehman, A., Ma, H., Irfan, M., & Ahmad, M. (2020). Does carbon dioxide, methane, nitrous oxide, and GHG emissions influence the agriculture? Evidence from China. *Environmental Science and Pollution Research*, 27(23), 28768–28779.
- Rohila, A. K., Maan, D., Kumar, A., & Kumar, K. (2017). Impact of agricultural practices on environment. *Asian J. of Microbiol. Env. Sc*, 19(2), 145–148.
- Ruszkiewicz, J. A., Tinkov, A. A., Skalny, A. V., Siokas, V., Dardiotis, E., Tsatsakis, A., Bowman, A. B., da Rocha, J. B., & Aschner, M. (2019). Brain diseases in changing climate. *Environmental Research*, 177, 108637.
- Sanogo, I., & Amadou, M. M. (2010). Rice market integration and food security in Nepal: The role of cross-border trade with India. *Food Policy*, 35(4), 312–322.
- Sarker, M. A. R., Alam, K., & Gow, J. (2014). Assessing the effects of climate change on rice yields: An econometric investigation using Bangladeshi panel data. *Economic Analysis and Policy*, 44(4), 405–416.
- Shi, J., Visschers, V. H., Bumann, N., & Siegrist, M. (2018). Consumers' climate-impact estimations of different food products. *Journal of Cleaner Production*, 172, 1646–1653.

- Shrestha, R. P., & Nepal, N. (2016). An assessment by subsistence farmers of the risks to food security attributable to climate change in Makwanpur. *Nepal. Food Security*, 8(2), 1–11.
- Sossou, S., Igue, C. B., & Diallo, M. (2019). Impact of climate change on cereal yield and production in the Sahel: Case of Burkina Faso. *Asian Journal of Agricultural Extension, Economics & Sociology*, 37(4), 1–11.
- Suvedi, M., Ghimire, R., & Kaplowitz, M. (2017). Farmers' participation in extension programs and technology adoption in rural Nepal: A logistic regression analysis. *The Journal of Agricultural Education and Extension*, 23(4), 351–371.
- Tao, F., Yokozawa, M., Xu, Y., Hayashi, Y., & Zhang, Z. (2006). Climate changes and trends in phenology and yields of field crops in China, 1981–2000. *Agricultural and Forest Meteorology*, 138(1–4), 82–92.
- Tao, S., Monteiro, A. P. A., Thompson, I. M., Hayen, M. J., & Dahl, G. E. (2012). Effect of late-gestation maternal heat stress on growth and immune function of dairy calves. *Journal of Dairy Science*, 95(12), 7128–7136.
- Tao, M., Chen, L., Xiong, X., Zhang, M., Ma, P., Tao, J., & Wang, Z. (2014). Formation process of the widespread extreme haze pollution over northern China in January 2013: Implications for regional air quality and climate. *Atmospheric Environment*, 98, 417–425.
- Tesfaye, K., Zaidi, P., Gbегbelegbe, S., Boeber, C., Getaneh, F., Seetharam, K., Erenstein, O., & Stirling, C. (2017). Climate change impacts and potential benefits of heat-tolerant maize in South Asia. *Theoretical and Applied Climatology*, 130(3), 959–970.
- United Nation, United Nations in Western Europe – UN 2020. 2010–2019 confirmed as warmest decade in history.
- Vaidya, S. (2020). Agriculture, data stories: Investment gap in agriculture. Nepal Outlook. Retrieved from <https://nepaloutlook.com/data-stories/investment-gap-in-agriculture/>. Accessed on December 18, 2021.
- Van Nguyen, N., & Ferrero, A. (2006). Meeting the challenges of global rice production. *Paddy and Water Environment*, 4(1), 1–9.
- Vij, S., Biesbroek, R., Groot, A., & Termeer, K. (2018). Changing climate policy paradigms in Bangladesh and Nepal. *Environmental Science & Policy*, 81, 77–85.
- Waha, K., Krummenauer, L., Adams, S., Aich, V., Baarsch, F., Coumou, D., Fader, M., Hoff, H., Jobbins, G., & Marcus, R. (2017). Climate change impacts in the Middle East and Northern Africa (MENA) region and their implications for vulnerable population groups. *Regional Environmental Change*, 17(6), 1623–1638.
- Warsame, A. A., Sheik-Ali, I. A., Ali, A. O., & Sarkodie, S. A. (2021). Climate change and crop production nexus in Somalia: an empirical evidence from ARDL technique. *Environmental Science and Pollution Research*, 28(160), 19838–19850.
- World Bank. (2020). Population, total – Nepal. The World Bank. Retrieved from <https://data.worldbank.org/indicator/SP.POP.TOTL?locations=NP>. Accessed on December 18, 2021.
- Xie, W., Huang, J., Wang, J., Cui, Q., Robertson, R., & Chen, K. (2018). Climate change impacts on China's agriculture: The responses from market and trade. *China Economic Review*.
- You, L., Rosegrant, M. W., Wood, S., & Sun, D. (2009). Impact of growing season temperature on wheat productivity in China. *Agricultural and Forest Meteorology*, 149(6–7), 1009–1014.
- Zaied, Y. B., & Cheikh, N. B. (2015). Long-run versus short-run analysis of climate change impacts on agricultural crops. *Environmental Modeling & Assessment*, 20(3), 259–271.
- Zhai, S., Song, G., Qin, Y., Ye, X., & Lee, J. (2017). Modeling the impacts of climate change and technical progress on the wheat yield in inland China: An autoregressive distributed lag approach. *PLOS ONE*, 12(9), e0184474.
- Zhang, T., & Yao, H. (2013). Estimating the impacts of warming trends on wheat and maize in China from 1980 to 2008 based on county level data. *International Journal of Climatology*, 33(3), 699–708.

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