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Impact of climate change on food security in India: an evidence from autoregressive distributed lag model

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Abstract

Food security is a critical global issue, particularly in India, and it is further exacerbated by the challenges posed by climate change. This study aims to examine the influence of climate change on food security in India, utilizing annual time series data spanning from 1994 to 2019. Using the Autoregressive Distributed Lag (ARDL) method, the study investigates the relationship between climate variables, area under cultivation, population growth, agricultural subsidies, and food production. The findings indicate that expanding the cultivation area for food crops significantly enhances food security, with a 1% increase leading to a 2.4% increase in the short run and a 3.2% increase in the long run. Conversely, population growth has a detrimental effect on food security, with a 1% increase resulting in a decline of 3.8% in the short run and 7.8% in the long run. Climate variables also play a crucial role, as rising temperatures adversely impact food security, leading to a decrease of 1.2% in the short run and 1.7% in the long run for every 1% temperature increase. Rainfall, on the other hand, does not significantly affect food security in the long run, but a decrease in rainfall in the preceding period negatively impacts food security in the short run. Furthermore, agricultural subsidies, particularly fertilizer subsidies, impact food security positively in the short run but have adverse effects in the long run. The study highlights the importance of sustainable land management, temperature control measures, water reservation, and effective agricultural subsidies to address food security challenges. These findings provide valuable insights for policymakers in designing effective strategies to ensure food security in India.

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1 Introduction

Food security is defined as ensuring that all people, at all times, have physical and economic access to sufficient, safe, and nutritious food to meet their dietary needs and food preferences for an active and healthy life (Bhuyan et al., 2020a; FAO, 1996; FAO WFP & IFAD, 2012). Food security is necessary for human beings because it ensures the smooth development of cognitive skills in the early and later stages of human life. Ensuring food security is one of the Sustainable Development Goals (i.e., Goal 2), which aims to end hunger and all forms of malnutrition by 2030. The quality of human capital, which is very crucial for the rise in the long-run productivity of an economy, is adversely affected by food insecurity. Food insecurity has been increasing in India, and more than half of the population is undernourished in India (Bhuyan et al., 2020b; Bhuyan et al., 2020c). India had the "second-highest estimated number of undernourished people in the world" (FAO, 2015, p.15). The most important pathway to reduce the level of food insecurity is ensuring a high level of agricultural food production (Mozumdar, 2012). Therefore, food insecurity has been an important issue for academicians and policymakers across the globe, especially in India.

In recent years, the issue of climate change has gained prominence alongside food security concerns. The rapid growth of the global population has been the primary driver of anthropogenic activities that contribute to climate change, including land use changes, deforestation, industrialization, transportation, and excessive water consumption (IPCC, 2014; Khatri & Tyagi, 2015). These anthropogenic activities also generate various types of waste that pose a burden on the environment. However, by reusing such waste, it is possible to alleviate the environmental impact (Abdelzaher et al., 2023; Abdelzaher and Shehata 2022; Benjeddou et al., 2023; Elkhouly et al., 2021; Owaid et al., 2022). These anthropogenic activities have increased greenhouse gasses, influencing climate change (IPCC, 2014). According to a study on the projected climate impact, global cereal production, including maize and wheat, is expected to decrease by 3.8% and 5.5%, respectively (Lobell et al., 2011).[1]

India has been highly susceptible to the impacts of climate change, experiencing recurring shocks such as floods, cyclones, and droughts (GOI, 2016).[2] Consequently, it has gained recognition as one of the most vulnerable countries in the world (Datta & Behera, 2022).[3] Previous studies have extensively documented the significant rise in temperature, heatwaves, droughts, floods, and intense cyclones in India (Datta & Behera, 2022;

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[1] The major crops production such as wheat, rice, maize, and soybean are susceptible to changes in mean air temperature in Southeast Asia (Liu et al., 2020). Similarly, an Indian study predicted a decline of 2.5% in wheat production compared to the base year 2013–14 due to climate change (Amita and Surender 2020). Such reductions in agricultural production are likely to exacerbate food insecurity levels in India.

[2] According to this report, drought-like situations occurred in India during the years 2002–03, 2009–10, 2014–15, and 2015–16 (GOI, 2016). These droughts have led to a decline in food consumption, forcing rural populations in Odisha, India, to adopt coping strategies (Sam et al., 2020). Unfortunately, such coping strategies often contribute to an increase in food insecurity levels.

[3] In fact, approximately 74% of districts in India are affected by this climate variability. Source: https://theprint.in/environment/74-of-indias-districts-prone-to-extreme-climate-like-droughts-floods-cyclones-says-study/756813/ Accessed on 8th /August/2022 at 11.44 p.m.

Ray et al., 2019; Rohini et al., 2016; Sharma & Mujumdar, 2017). In India, the average temperature, as measured by sea surface area in the oceanic region and near-surface air temperature in the land areas, has increased by 0.7% between 1901 and 2018 (Krishnan et al., 2020).[4] These temperature changes are likely to disrupt crop production due to irregularities in monsoon patterns, as 84% of India's total precipitation is contributed by summer monsoon rainfall (Saha et al., 2014).[5] Consequently, climate change has a substantial impact on agricultural production, leading to variability in output and thus affecting food security (Kumar and Sharma 2013).

Numerous studies in the literature have explored the effects of climate change on agricultural production using various analytical approaches. Time series analysis has been utilized in studies conducted by Barrios et al. (2008), Ben Zaied and Zouabi (2015), Chandio et al., (2020a, 2020b), Dumrul and Kilicaslan (2017), Onour (2019), Warsame et al. (2021), and Zhao et al. (2017). Additionally, panel data analysis has been employed in research by Ali et al. (2017), Kumar et al. (2021), Kumar and Upadhyay (2019), Loum and Fogarassy (2015), and Sarker et al. (2014). However, the majority of these studies have focused on countries other than India. In the Indian context, there have been a few studies examining the impact of climate change on agricultural production. These studies include the works of Ahmad et al. (2011), Baig et al. (2020), Birthal et al. (2014), Rao et al. (2016), Guntukula (2020), Kumar et al. (2017), Praveen and Sharma (2020), and Singh et al. (2019). However, these studies have often considered specific crops or multiple crop production as the output variable in their regression analyses. Such an approach fails to capture the comprehensive picture of agricultural output. Furthermore, these studies have not incorporated recent years' data in their analyses, and their results have shown diverse outcomes in terms of sign, magnitude, and significance levels.

To the best of our knowledge, no study has yet considered the food production index as a proxy for food security. Additionally, the influence of agricultural subsidies, an important predictor of agricultural production, has been largely overlooked by previous studies. Hence, there is a pressing need for further investigation to address these gaps in the existing literature in India. To address the research gap, this study examines the impact of climate change on food security in India. More specifically, we establish the following objectives: (a) to assess the impact of climate change on food production, and (b) to examine the role of agricultural subsidies, specifically fertilizer subsidies, in food production. To address these objectives, the study employs the Autoregressive Distributed Lag (ARDL) method.[6]

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[4] Furthermore, the report highlights that during the period of 1986–2015, the temperature of the coldest night increased by approximately 0.4%, while the temperature of the warmest day rose by around 0.63% (Krishnan et al., 2020).

[5] The recent Food and Agriculture Organization (FAO) report shows that about 70 percent of the rural population relied on agricultural activities to provide life and livelihood. Besides, the report also revealed that 82 percent of the farmers are small and marginal. These small and marginal farmers often depend on the monsoon because rainfall is the primary water source for irrigation in agricultural activity. Due to natural and anthropogenic activities, climate change likely affected the temperature and rainfall. As a result, there is a chance of adverse impact on the agricultural sector, and hence, food security.

[6] This method can be used for the combination of stationary and non-stationary time series, which is most advantage comparative to the other time series modeling. It provides information on the short-run and long-run impact of the predictors of importance. It is efficient in small samples. Additionally, it also reports the error correction mechanism which shows the speed of adjustment to move from disequilibrium to the equilibrium in the short-run. Due to above importance, the present study used ARDL method to examine our objective.

The present research paper carries forward the existing literature by contributing as follows: Firstly, we include the food production index, representing all types of food production, as the dependent variable, and incorporate agricultural subsidies as an independent variable in the regression analysis. This comprehensive approach provides a more holistic understanding of the relationship between these factors. Secondly, using the ARDL method, the study has employed a very long period of the dataset covering the most recent data up to 2019, which has not been widely explored in the Indian context. Lastly, given the increasing levels of food insecurity in India, it is crucial to reevaluate the role of climate change in food security. Our study aims to bridge this gap by examining the impact of climate change on food security in India. These factors make this study particularly valuable for policymakers, providing them with essential insights for policy analysis.

The remaining sections of this study are structured as follows: Sect. 2 provides a brief review of the existing literature. Section 3 explains the conceptual framework, while Sect. 4 describes the data and methodology used in the study. The results and discussion are presented in Sect. 5, followed by the conclusion, policy implications, limitations, and future scope in Sect. 6.

2 Review of literature

In this section, we provide a brief overview of existing research on the impact of climate change on agricultural output. Climate change poses a significant challenge to food security and human development as it affects the productivity and production patterns of agricultural output (Arora, 2019). Therefore, the development of the agricultural sector is crucial for economic growth as it ensures unskilled employment, addresses food insecurity, and provides income to impoverished populations (Dethier & Effenberger, 2012). The increase in economic growth further matters for the change in the productivity and efficiency of the financial sectors like banks (Bhuyan et al., 2022; Das & Patra, 2016a, 2016b) and stock markets (Bhuyan et al., 2020d; Patra & Hiremath, 2022) which proves the close link between the development of the agricultural sector and non-agricultural economy (Timmer, 1995), especially the financial sector (Grivins et al., 2021).

Several past studies have explored the relationship between climate change and food security. For instance, Kotir (2011) conducted a review on the scope and nature of climate change and its impact on food production and food security in sub-Saharan Africa. The findings revealed that climate change is already evident through changing temperatures and rainfall patterns. The study also highlighted the adverse impact of climate change on the agricultural sector. Similarly, Sarker et al. (2014) found that climate change increases the risk to rice production in Bangladesh. Demeke et al. (2011) examined the impact of rainfall on the food security of rural households in Ethiopia and identified an adverse impact.

Examining the relationship between climate change and cotton production in Pakistan, Abbas (2020) utilized the ARDL model and found that increasing average temperatures have a positive but insignificant impact on cotton production. Additionally, the study indicated that the area under cultivation and fertilizer consumption positively influence cotton production in both the short and long run. In Japan, Tokunaga et al. (2015) discovered that rising temperatures negatively affected rice, vegetable, and potato production. Barrios et al. (2008) observed that while rainfall positively affects agricultural production, temperature has an adverse impact in sub-Saharan Africa. Furthermore, their interaction was found to have a detrimental effect on production. Bandara and Cai (2014) identified a negative

impact on food production and prices resulting from climate-induced agricultural productivity changes in South Asia.

The previous literature highlights that variations in mean temperature and rainfall are important factors of climate change, which can significantly impact agricultural production. As a result, when the agricultural sector is affected, food insecurity increases due to a shortage of food supply. Few studies have examined the impact of climate change on agricultural production in India. Some of them found a positive impact, whereas others found a negative impact (Kumar and Sharma 2013). There are also mixed impacts on food production (Baig et al., 2020; Chandio et al., 2020a, 2020b; Guntukula, 2020). On the other hand, Janjua et al. (2014) found no significant impact. Moreover, a recent study by Amita and Surender (2020) examined the climate impact on wheat production in India using a balanced panel of crop-level data from 118 districts, spanning from 1998 to 2014. They revealed that wheat production is projected to decline by 2.35 percent due to climate change. However, these studies utilized older data and did not capture recent years. Given the increasing level of food insecurity in India, there is a need to revisit the role of climate change on food security using more recent data. The present study aims to fill this gap by examining the impact of climate change on food security in India.

3 Conceptual framework

Before proceeding with our empirical strategies, this section presents the conceptual linkage between climate change and food security (refer to Fig. 1). The figure illustrates how various components of climate change, including CO_2 levels, temperature, precipitation, extreme weather conditions, and weather variability, directly influence different activities within the food system. For example, an increase in maximum temperatures on hot days and minimum temperatures on cold days adversely affects cultivation and harvesting activities, leading to a potential decline in food grain production. Similarly, variations in irrigation and rainfall patterns pose obstacles to the growth of food crops, affecting timely cultivation and harvesting. Rainfall variations also impact activities related to storage, processing, and distribution. When food system activities are disrupted by climate change, it has a direct adverse effect on food system assets.

For instance, decreased food production activities directly impact the overall output of food grains, while declines in storing, processing, and distributing activities reduce the infrastructure related to storage, marketing, transportation, and food preparation assets. These food system assets, in turn, influence different dimensions of food security, such as food availability, accessibility, utilization, and overall system stability. Any variation in these components can significantly alter the overall level of food security.

Furthermore, population growth contributes to climate change by accelerating deforestation, industrialization, and urbanization. As the population increases, there is a higher dependence on agriculture for sustenance and livelihood. Consequently, this increased pressure on the agricultural sector further influences food system activities, food system assets, and the various components of food security. In summary, Fig. 1 provides a brief overview of the pathway from climate change to food security, highlighting the essential role of climate change in influencing food security outcomes.
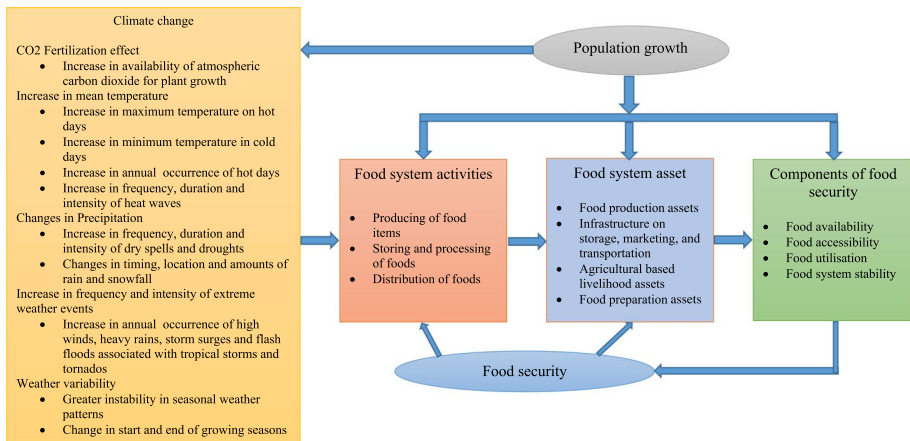
Fig. 1 Schematic diagram connecting climate change and food security. The above figure is the modified version of FAO (2008)

4 Method

4.1 Study area

This study focuses on India, which is classified as a lower-middle-income country according to the World Bank classification. India is the second most populous country in the world, following China.[7] It spans between latitudes 8° 4' and 37° 6' North of the Equator and longitudes 68° 7' and 97° 25' East of it.[8] The majority of households in India rely on agricultural activities, which account for approximately 70% of the population's livelihoods.

Figure 2 depicts the decade-wise trend of constructed large dams in India. The Indian government, in collaboration with state governments, has constructed 5254[9] large dams across different states to enhance water reserve capacity for agricultural activities and electricity production. Additionally, there are currently 447 large dams under construction. Notably, the highest number of large dams were completed during the period from 1981 to 1990 (Fig. 2). However, India has been experiencing the frequent impacts of climate change, such as droughts, floods, and high temperatures (Government of India, n.d.; Singh, 2016).

India is divided into several agro-climatic zones based on local climatic conditions and agricultural practices (Choudhary & Sirohi, 2022). These agro-climatic zones, as presented in Fig. 3 based on Choudhary and Sirohi (2022), help in understanding the agricultural potential and suitability of various crops across the country. Each region is associated with unique terrains, soil types, climates, and agricultural patterns. For example, agriculture

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[7] The information is obtained from https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups on 08th/Sept/2022 at 5.23 p.m.

[8] The information is obtained from following website https://www.india.gov.in/india-glance/profile on 08th/Sept/2022 at 4.35 p.m.

[9] The information is obtained from http://cwc.gov.in/sites/default/files/NRLD_04012017.pdf on 30th/Sept/2022 at 6.15 p.m.
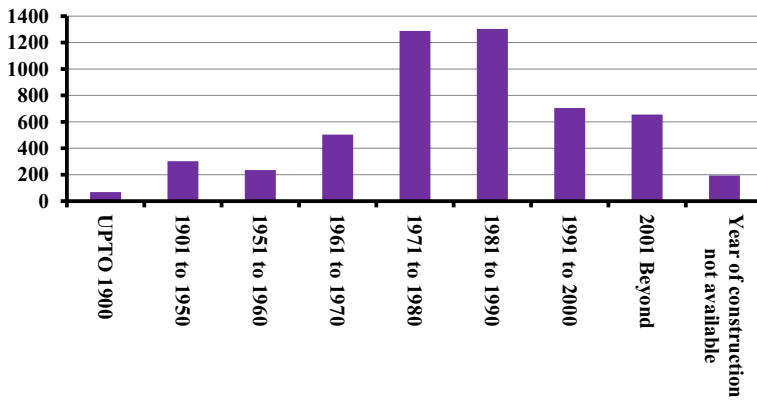
Fig. 2 Large dams (Decade wise)

in the western Himalayan region, which includes Himachal Pradesh, Jammu & Kashmir, and Uttarakhand, is primarily rain dependent. Rice, wheat, and maize are important cereal crops in this region (Fig. 3).

4.2 Data

The present study has used the food production index as a proxy for food security. The food production index reflects the output level of all available food crops. Average rainfall and average temperature were used as proxies for climate change. Population growth, areas of food crop cultivation, and fertilizer subsidy were considered as additional independent variables in the analysis. The annual data used for the study range from 1994 to 2019, based on data availability.

The food production index is based on the base year of 2007–08, with a value of 100. The average temperature was measured by considering the minimum and maximum temperatures for each year. Rainfall data represent the overall rainfall from June of the previous year to May of the current year. For example, the rainfall data for 1994 represent the cumulative rainfall from June 1993 to May 1994. Population growth was measured as a percentage change. Table 1 provides the variable names, symbols, units of measurement, and sources used in the analysis. All variables, except population growth, were transformed into natural logarithms prior to the econometric analysis.

4.3 Econometric analysis

4.3.1 ARDL model specification

This study used a novel method, namely ARDL to examine between dependent variable and independent variable of the regression analysis. The ARDL bounds testing approach to the cointegration method, developed by Pesaran et al. (2001), is used to examine the long-run relationship among the variables. The novel advantage of this method is that it can be
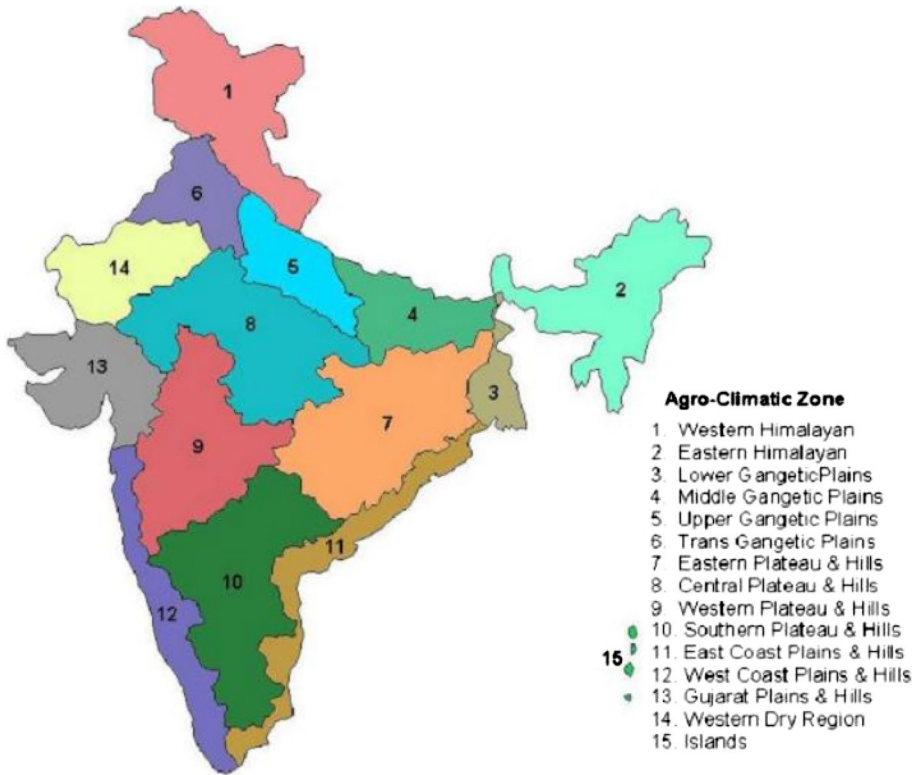
Fig. 3 Agro-climatic Zones of India. Source: https://vikaspedia.in/agriculture/crop-production/weather-information/agro-climatic-zones-in-india accessed on 13th/June/2023 at 12.03 a.m

applied to the time series irrespective of the order of integration.[10] More specifically, this method is more robust because it can be used if the variables are I(0) or I(1) or mixed I(0) and I(1). Besides, the ARDL model is efficient in small samples. However, it cannot be applied in the presence of I (2) time series. The present study has used the following specification of the ARDL models,

$$\Delta\text{LFPI}_t = \alpha_0 + \beta_1\text{LFPI}_{t-1} + \beta_2\text{LAUFGP}_{t-1} + \beta_3\text{PPG}_{t-1} + \beta_4\text{LRF}_{t-1} + \beta_5\text{LTP}_{t-1} + \beta_6\text{LFS}_{t-i}$$

$$\sum_{i=1}^{m}\Phi_1\Delta\text{LFPI}_{t-i} + \sum_{i=0}^{m}\Phi_2\Delta\text{LAUFGP}_{t-i} + \sum_{i=0}^{m}\Phi_3\Delta\text{PPG}_{t-i} + \sum_{i=0}^{m}\Phi_4\Delta\text{LRF}_{t-i} +$$

$$\sum_{i=0}^{m}\Phi_5\Delta\text{LTP}_{t-i} + \sum_{i=0}^{m}\Phi_6\Delta\text{LFS}_{t-i} + \varepsilon_t$$

(1)

where LFPI, LAUFGP,PPG,LRF, LTP, and LFS are the natural logarithm of the food production index, areas under food grain production, population growth, average rainfall,

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[10] The order of integration in time series, denoted as "I(d)," refers to the number of times required to be differentiable to become stationary. Stationarity of time series refers to the certain condition fulfilment such as the mean, variance, and covariance should be time invariant. If the time series is stationary at level, it is represented as I(0) whereas if the time series is stationary at first difference, it is denoted as I(1).

Table 1 Description of variables

Variables	Symbol	Unit	Sources
Food production index*	FPI	N.A	Reserve Bank of India
Areas under food grain production*	AUFGP	N.A	Reserve Bank of India
Population growth	PPG	NA	World Development Indicators
Rainfall	RF	Millimeter (mm)	Indiastat.com
Temperature	TP	Degree in Celsius	Indiastat.com
Fertilizer subsidy	FS	Rupees in Crores	Indiastat.com

*Indicates an index (base year 2007–08 = 100). N.A indicates not available because the index is unit-free

average temperature, and fertilizer subsidy, respectively. The subscript t indicates the time in years. The coefficients and error term are presented in the form of α, β, Φ, and ε_t, respectively.

4.3.2 Bounds testing approach

The Wald test (F-statistics) is applied to identify a long-run relationship after estimating Eq. (1) using ordinary least squares (OLS). This test imposes a linear restriction on the one-period lagged variables. The null hypothesis is no cointegration,[11] whereas the alternative hypothesis is cointegration among variables. The null and alternative hypotheses of the above model to conduct the bounds test are below,

$H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = 0$ (No long-run relationship)

$H_1 : \beta_1 \neq 0, \beta_2 \neq 0, \beta_3 \neq 0, \beta_4 \neq 0, \beta_5 \neq 0, \beta_6 \neq 0$ (Long-run relationship exists)

The lower and upper bound critical values of F-statistics have been provided by Pesaran et al. (2001). The lower bound critical value assumes that explanatory variables are integrated of order zero[I(0)] in the bound testing approach. In contrast, the upper bound critical value assumes that it is of order one [I(1)]. The null of no long-run relationship will be accepted if the estimated F-values are smaller than the lower critical bound value. On the contrary, the alternative hypothesis will be accepted if the F-value lies above the upper bound critical value. The cointegration decision will be inconclusive if the F-values fall between lower and upper-bound critical values. After the cointegration is confirmed, the long-run and short-run relationships are estimated using the following equations.

The long-run equation is:

$$
\begin{aligned}
\text{LFPI}_t = {} & \alpha_0 + \sum_{i=1}^{m} \beta_1 \text{LFPI}_{t-i} + \sum_{i=0}^{m} \beta_2 \text{LAUFGP}_{t-i} \\
& + \sum_{i=0}^{m} \beta_3 \text{PPG}_{t-i} + \sum_{i=0}^{m} \beta_4 \text{LRF}_{t-i} + \sum_{i=0}^{m} \beta_5 \text{LTP}_{t-i} + + \sum_{i=0}^{m} \beta_6 \text{LFS}_{t-i} + \varepsilon_t
\end{aligned}
\tag{2}
$$

Then, the parameters' short-run dynamics are estimated using the following error correction mechanisms equation.

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[11] Cointegration between time series refers to the fact that the time series moves together in long-run without the divergency from each other.

$$\Delta \text{LFPI}_t = \alpha_0 + \sum_{i=1}^{m} \Phi_1 \Delta \text{LFPI}_{t-i} + \sum_{i=0}^{m} \Phi_2 \Delta \text{LAUFGP}_{t-i} + \sum_{i=0}^{m} \Phi_3 \Delta \text{PPG}_{t-i}$$

$$+ \sum_{i=0}^{m} \Phi_4 \Delta \text{LRF}_{t-i} + \sum_{i=0}^{m} \Phi_5 \Delta \text{LTP}_{t-i} + \sum_{i=0}^{m} \Phi_6 \Delta \text{LFS}_{t-i} + \xi ECM_{t-1} + \varepsilon_t \tag{3}$$

In the above equations, Δ is the first difference operator, α_0 is the intercept, β_i and Φ_i are the coefficients, ECM_{t-1} is the one period lagged error correction term, ξ is the speed of adjustment, and ε is the error terms of the model. The definitions of variables are similar to Eq. (1).

5 Results and discussion

In this section, we first examine the summary statistics and trend analysis of the variables. Subsequently, we present the econometric results and provide discussions.

5.1 Trend analysis and descriptive statistics

Figure 4a, b, c, d, e, and f presents the time series plots of the food production index, food grain production area index, population growth, rainfall, average temperature, and fertilizer subsidy, respectively. It is observed that the food grain production (Fig. 4a) and the area of food grain production (Fig. 4b) have been increasing since 1994. However, a decline in the food production index was observed in 2003, which can be attributed to a drought-like situation across the country during 2002–03, resulting in a significant decrease in rainfall (GOI, 2016). Similarly, drought situations in 2009–10, 2014–15, and 2015–16 led to declines in food grain production in those years (GOI, 2016). A declining trend was observed in the annual percentage of population growth (Fig. 4c). This trend may be attributed to improvements in literacy, awareness, and economic conditions, which have lowered the birth rate and fertility. It also reflects the impact of the proactive implementation of family planning measures, ensuring universal access to sexual and reproductive healthcare services and counseling information (Muttreja & Singh, 2018).

Regarding climatic variables, rainfall (Fig. 4d) has shown a declining trend, while there is an increasing trend in temperature (Fig. 4e). The decline in average rainfall can be explained by the weakening of the summer monsoon, which is a crucial water source for agriculture in India (GOI, 2016). These results align with previous findings that estimated a 6% decline in summer monsoon precipitation in India from 1951 to 2015 (Krishnan et al., 2020). Fertilizer subsidy has been increasing since 1994 (Fig. 4f), indicating proactive government engagement to enhance food production and food security. Notably, there was a significant increase in fertilizer subsidies in 2008. This rise in subsidy can be partly attributed to the increasing import prices of fertilizers. Despite the increase in international prices, the Government of India did not raise the Maximum Retail Price (MRP) of fertilizers. Instead, it announced a substantial subsidy amount to support farmers and domestic fertilizer producers, mitigating the cost difference due to the international price increase.

Descriptive statistics of the variables are presented in Table 2. The findings reveal that the mean of the food production index (LFPI) and area under food grain production (LAUFGP) are similar, but the standard deviation of LFPI is larger, indicating higher volatility in LFPI compared to LAUFGP. LAUFGP exhibits negative skewness, while

LFPI shows positive skewness. Kurtosis statistics indicate that LFPI is platykurtic, while LAUFGP is leptokurtic. The mean of population growth (PPG) is 0.377, with a standard deviation of 0.216. It exhibits negative skewness and follows the leptokurtic distribution. Among the climate change variables, rainfall (LRF) has a higher mean and standard deviation compared to temperature (LTP). Both rainfall and temperature exhibit negative skewness and platykurtic distribution. Fertilizer subsidy shows negative skewness.

5.2 Empirical analysis

5.2.1 Identifying order of integration

Table 3 presents the unit-root test results for the variables using the augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests. These tests are conducted to identify the order of integration of the time series data. The results show that LFPI, LAUFGP, LRF, LFS, and LTP are non-stationary at their levels but become stationary at the first difference. On the other hand, PPGis stationary at the level. This mixed order of integration, where most variables are integrated of order one and one variable is stationary at the level, is suitable for the ARDL model (Pesaran et al., 2001). Therefore, we proceed with the ARDL model estimation.

5.2.2 Bounds testing approaches for cointegration

In the second step, we conduct the ARDL bounds test to determine the presence of cointegration among the variables. The results of the bounds testing approach for cointegration are presented in Table 4. The null hypothesis of no cointegration is tested for the variables. The F-statistic in the estimated model is 9.993, which exceeds the critical values at the 1% significance level. As a result, we reject the null hypothesis of no cointegration, supporting the alternative hypothesis and suggesting the presence of cointegration among the variables. Our findings and decisions align with previous literature (Mohanty et al., 2020; Singh and Bhuyan, 2016).

5.2.3 Estimation of the long-run and short-run coefficients

Following the confirmation of cointegration from the bounds test, we estimate the long-run and short-run coefficients using the ARDL model. Table 5 presents the results of the long-run and short-run coefficients, with food production index as the dependent variable and area under cultivation, population growth, rainfall, temperature, and fertilizer subsidy as independent variables.

Agricultural production and food insecurity vary across countries due to the different levels of availability of resources and their utilization (Dethier & Effenberger, 2012). The long-run results reveal that the coefficient of areas under cultivation for food crops is positive and significant at the one percent level of significance; similar coefficients' signs and significance are found in the short run. This finding suggests that a one percent increase in the area under food grain production will lead to a 2.4% and 3.2% increase in food grain production in the short run and long run, respectively. These results are consistent with the findings of Guntukula (2020) and differ from the findings of Chandio et al., 2020a, 2020b.
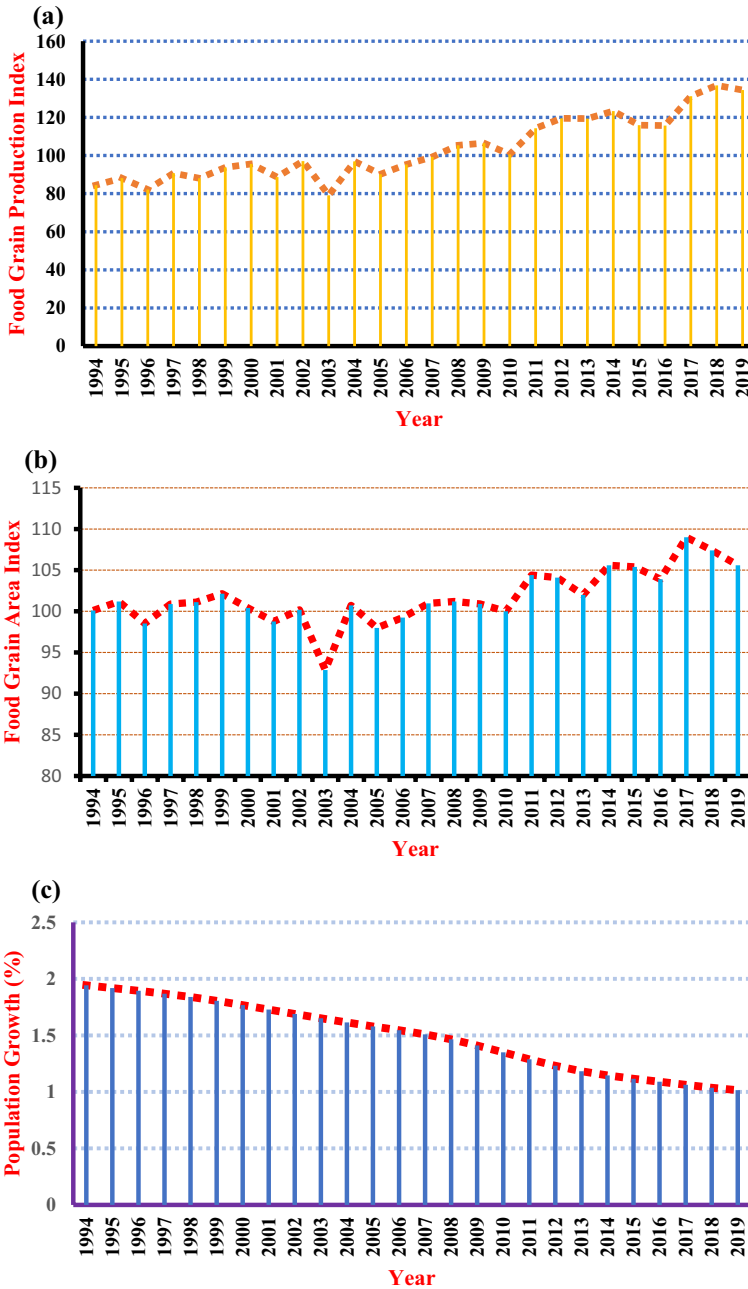
(a)

(b)

(c)

Fig. 4 Time series plot of variables

Also, due to the positive sign and statistical significance of the coefficient, our results do not support the finding of a previous study that argued that land constraints limit agricultural output (Kumar, 2021). Further, our short-run results are similar and long-run results
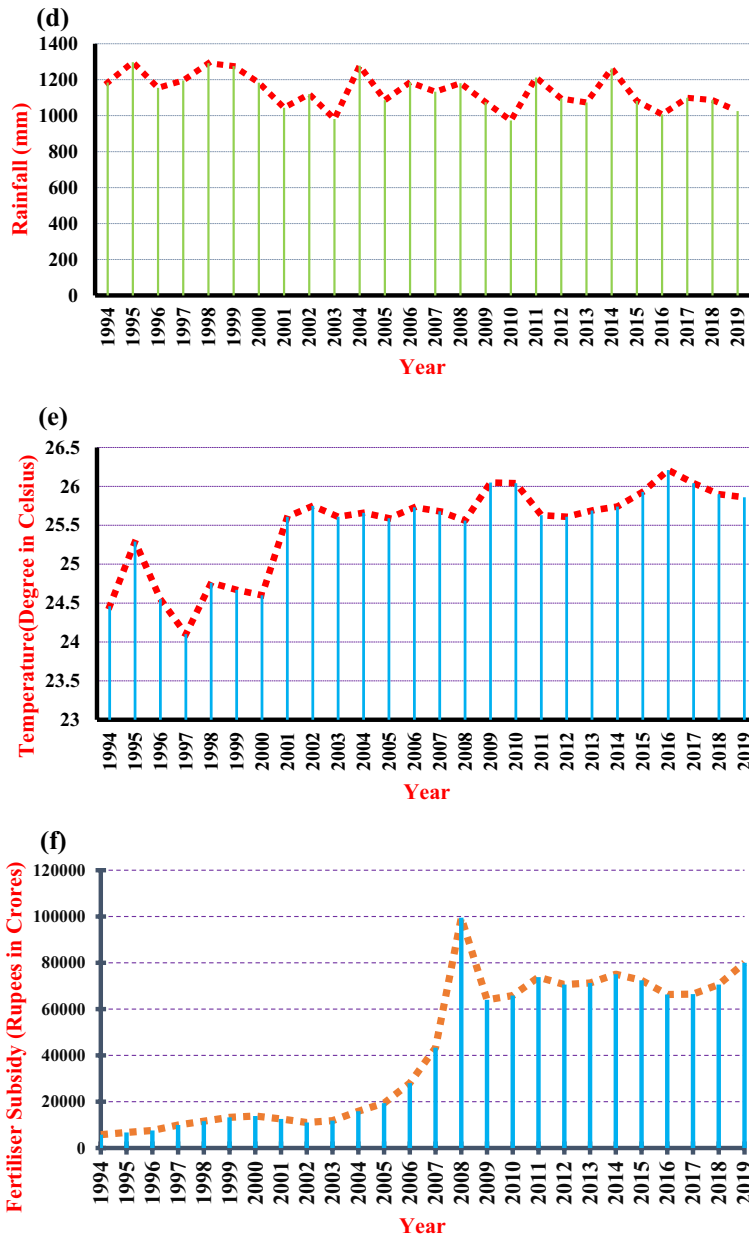
(d)

(e)

(f)

Fig. 4 (continued)

are opposing to the findings of (Janjua et al., 2014). From our results, we argued that effective utilization of available land can lead to higher output in the short run. In the long run, we can further increase production by converting barren land into arable land.

The coefficient of population growth is negative and significant in both the long run and short run, indicating that an increase in population will reduce food production and food

Table 2 Descriptive statistics

Variables/Statistic	Mean	Maximum	Minimum	S.D	Skewness	Kurtosis
Log of food production index (LFPI)	4.628	4.918	4.371	0.157	0.310	1.998
Log of area under food grain production (LAUFGP)	4.621	4.691	4.531	0.032	−0.197	3.949
population Growth (PPG)	1.491	1.943	1.015	0.310	−0.108	1.623
Log of rainfall (LRF)	7.033	7.168	6.880	0.084	−0.032	2.067
Log of temperature (LTP)	3.237	3.266	3.182	0.022	−1.044	2.877
Log of total fertilizer subsidy (LFS)	10.264	11.508	8.660	0.960	−0.214	1.401

S.D. refers to the standard deviation

Table 3 Unit root results

Variables/Test	ADF test		PP test		Decision
	Level	First difference	Level	First difference	
LFPI	2.10	−8.82***	1.78	−8.73***	I(1)
LAUFGP	1.26	−5.66***	1.08	−10.55***	I(1)
PPG	−1.63*	–	−7.02***	–	I(0)
LRF	−0.62	−5.92***	−1.23	−14.63***	I(1)
LTP	1.41	−2.85***	1.73	−6.51***	I(1)
LFS	−1.34	−4.14***	−1.34	−4.14***	I(1)

***, **, and * denote 1, 5, and 10 percent significance levels, respectively. Variable definitions are similar to Table 1

security. This may be attributed to the decrease in available land for cultivation due to population growth, leading to a decline in total output. Additionally, the higher dependence on agriculture and the increase in disguised unemployment may partially explain the adverse impact of population growth on food security.

The coefficient of rainfall is negative and insignificant in both the long run and short run, indicating that an increase in rainfall does not significantly impact food security. These results are consistent with the findings of Guntukula (2020) for food crops and Chandio et al., (2020a, 2020b). The variability in rainfall availability and the lack of storage and distribution facilities may partially explain this result. Previous studies have suggested that the increase in crop water demand due to prolonged warming requires more irrigation facilities (Datta & Behera, 2022). The short-run result indicates that the previous year's rainfall has a significant negative effect on food grain production, possibly due to uneven and untimely water distribution for cultivation.

The coefficients of temperature in both the long run and short run are negative and significant. This implies that a 1% increase in mean temperature will lead to a 1.7% reduction in food production in the long run and a 1.2% reduction in the short run. These results contradict the findings of Guntukula (2020), who used maximum and minimum temperatures as determinants for food crops. Our results regarding the impact of climate change, specifically increasing temperature, on food security align with previous studies (Barrios et al., 2008; Chandio et al., 2020a, 2020b, 2023; Warsame et al., 2021; Zhao et al., 2017). Additionally,

Table 4 Results of ARDL bound test

Model LFPI = f(LAUFGP, PPG, LRF, LTP, LFS)		

ARDL Bound Test:-F-statistic: 9.993***

Critical Value Bounds

Significance	Lower bound I(0)	Upper bound I(1)
10%	1.81	2.93
5%	2.14	3.34
1%	2.82	4.21

*** and ** denote 1% and 5% levels of significance, respectively

Table 5 Estimation of long-run and short-run coefficients using ARDL

LFPI = f(LAUFGP, PPG, LRF, LTP, LFS)

Selected Model: ARDL(1,0,1,2,0,2) based on Schwarz criterion (SIC)

Long Run Coeff				Short Run Coeff			
Variable	Coeff	S.E	Prob	Variable	Coeff	S.E	Prob
LAUFGP	3.298	0.760	0.001	ΔLAUFGP	2.423	0.314	0.000
PPG	−0.781	0.171	0.000	ΔPPG	−3.892	0.783	0.000
LRF	−0.342	0.345	0.340	ΔLRF	−0.155	0.102	0.151
LTP	−1.723	0.477	0.003	ΔLRF(−1)	−0.156	0.061	0.024
LFS	−0.165	0.063	0.021	ΔLTP	−1.208	0.429	0.015
				ΔLFS	0.0004	0.025	0.985
				ΔLFS(−1)	0.143	0.132	0.001
				$ECMT_{t-1}$	−0.626	0.252	0.018

***, **, and * denote 1, 5, and 10 percent significance levels, respectively. Coeff and S.E. refer to coefficients and standard error, respectively. ARDL refers to autoregressive distributed lag

a study revealed that agricultural production, such as rice, would have increased by 4% if warmer nights and less rainfall had not occurred (Auffhammer et al., 2012). Extreme weather events also have adverse consequences on GDP, with average crop losses resulting in a 0.25% loss of GDP. The error correction term is significant and negative, indicating that disequilibrium can move toward equilibrium at a rate of 64.7% in the short run.

5.2.4 Diagnostic and stability test of the ARDL models

Diagnostic tests for the ARDL model are presented in Table 6. These tests include the serial correlation test, normality test, heteroscedasticity test, ARCH test, and Ramsey RESET specification test. The serial correlation test, which examines the null of no-cereal correlation, is statistically insignificant at a one percent level of significance. So, the hypothesis is rejected, and there is no issue of serial correlation in the estimated model. Like Mohanty et al. (2020), we also carried out other diagnostic tests such as the Normality test, Heteroscedasticity Test, ARCH test, and Ramsey RESET specification tests. The

results of these diagnostic test show that the estimated models have passed all the diagnostic tests (Table 6).

After conducting the necessary diagnostic tests, we assess the stability of the model using the cumulative sum (CUSUM) and cumulative sum of squares (CUSUM SQ). The CUSUM and CUSUM SQ are plotted and shown in Fig. 5. Both the CUSUM and CUSUM SQ plots lie within the upper and lower bounds of the five percent significance level, indicating the stability of the model. Overall, the diagnostic tests (Table 6) and model stability plot (Fig. 5) conclude that the estimated model fits well, and there are no issues in the model estimates.

6 Conclusion, policy implications, limitations, and future scope

Achieving food security, as outlined in SDG Goal 2, is a significant challenge for many countries worldwide. Food security is crucial for reducing hunger, addressing malnutrition, and promoting the cognitive development of individuals. It also plays a vital role in raising the long-term productivity of economies through the development of quality human capital. However, climate change poses substantial challenges to achieving food security due to increasing temperatures, changing precipitation patterns, and more frequent extreme events such as severe warming, floods, and droughts. This study aimed to fill the gap in understanding the impact of climate change and other crucial variables on food security in India. Using annual time series data from 1994 to 2019 and employing the ARDL bounds testing approach, we investigated the relationship between climate change and food security.

The findings indicate that the area under cultivation for food crops significantly improves food security, while population growth has an adverse effect in both the long and short run. Among the climate variables, temperature significantly decreases food security in both the long and short run, while rainfall has no significant impact on food security in the long run. However, rainfall was found to have a negative impact on food production in the short run, particularly with a one-period lag, suggesting issues with water distribution for food grain production. The previous year's fertilizer subsidy positively impacts food security in the short run but has a negative effect in the long run. The study highlights climate change and population growth as major obstacles to achieving food security, emphasizing the need for comprehensive strategies. Although the area under food crop production has a favorable impact on food security, high population growth will put pressure on the diversion of arable land into non-agricultural activity, a serious challenge for achieving food security.

To address these challenges, the Government of India has been implementing a variety of direct and indirect policies to combat food insecurity. Direct interventions, such as the Public Distribution System (PDS) and the Midday Meal Scheme, and indirect policies like the creation of income-generating unskilled employment opportunities such as MGN-REGA have been implemented. However, these programs alone are insufficient to achieve Goal 2 of the SDGs by 2030 unless they specifically address the impact of climate change. Therefore, based on the results of this research, we have learned the following key lessons: a) Population control is necessary in conjunction with food assistance programs such as the PDS and implementing acts like the National Food Security Act, 2013, to achieve food security, b) the cultivation area should be expanded with a focus on encouraging organic farming, which will reduce environmental degradation and increase food production, c) temperature control is essential, and adopting a "go green" initiative can promote food

Table 6 Diagnostic tests results

Diagnostic tests	Statistics	P value
Serial correlation test	0.713	0.511
Normality test:	0.012	0.994
Heteroscedasticity test:	0.924	0.549
ARCH test:	0.157	0.670
Ramsey RESET test:	1.104	0.314

ARCH and Ramsey RESET tests refer to autoregressive conditional heteroscedastic test, and Ramsey regression equation specification error test, respectively. All statistics of diagnostic tests are F-statistic; however, the serial correlation test is Obs*R-squared
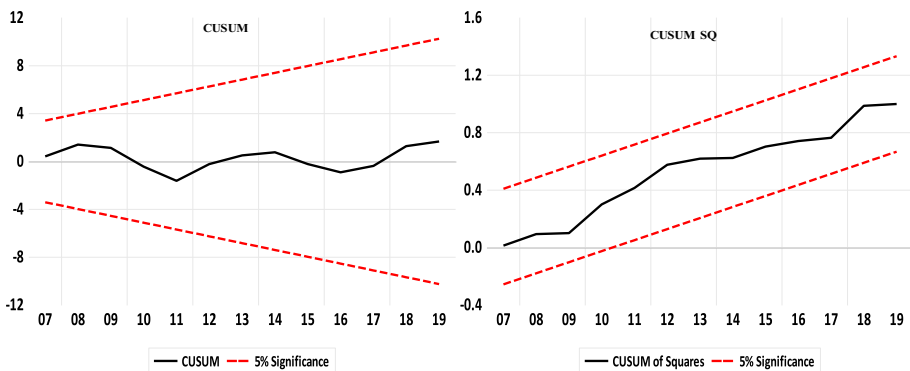

Fig. 5 Testing of the model stability. Source: Authors' computations. CUSUM: cumulative sum. CUSUM SQ: cumulative sum of squares

security, and d) proper utilization of rainwater, achieved by increasing investment in water reservation, is crucial to ensure food security.

The study highlights the importance of forward-looking environmental policies, such as restrictions on deforestation, increased surveillance of industrial operations, and urbanization with a focus on plantation, to control increasing temperatures and reduce food insecurity by enhancing food production. Additionally, increased investment in water reservation is crucial for efficient water resource utilization and ensuring food security. Policymakers might consider these findings to design effective agricultural policies that increase resilience to agricultural production and ensure food security.

However, this study has certain limitations. It is a macro-level analysis and unable to explore the micro-level impacts of climate change on food security. Future studies could focus on the specific micro-level impacts of climate change on food security in India. Additionally, the study did not examine the mediating role of industrialization between climate change and agricultural production. Further research can explore this relationship, as industrial activities can reduce agricultural land and environmental quality. Other variables for assessing climate change could be considered in future studies. Furthermore, employing modeling techniques like wavelet analysis in the time and frequency domain could provide a deeper understanding of the relationship between climate change and food security.

Author contributions BB was involved in conception and design, data collection and analysis, first draft of the manuscript and revision. RKM contributed to data collection and analysis and provided comments to improve the manuscript. SP was involved in conception and design, drafting and provided comments to improve the manuscript. All authors read and approved the final manuscript.

Data availability The datasets used in the analysis are available in the Indiastat.com, RBI, EPWRPF, and World Development Indicators repository.

Declarations

Conflict of interest We have no conflicts of interest to disclose.

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