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Effects of climate change on food security and sustainable development in Saudi Arabia: Autoregressive Distributed Lag approach

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Abstract. *This study examines the influence of climate change on Food security and sustainable development in Saudi Arabia from 1981 to 2022 using ARDL approach. Through the ecological footprint, alongside rainfall, population, agricultural growth, and GDP per capita. The results show a consistent negative impact of climate change on Food security in both the short and long run. Specifically, a 1% increase in the ecological footprint leads to a significant decline in Food security, confirming long-term structural vulnerabilities. These findings highlight the need for climate-resilient agricultural policies and sustainable resource management aligned with Saudi Vision 2030.*

Keywords: climate change, ecological footprint, food security, Saudi Arabia, Sustainable Development.

JEL Classification: Q54, Q56, Q18, O13, Q15.

I. Introduction

According to the World Economic Forum, climate change is a major global threat. Global temperatures have climbed by 1.2 degrees Celsius, and this warming trend is accelerating alarmingly. Scientists predict that temperatures could rise by approximately 5 degrees Celsius by the end of this century. Global temperatures are soaring at an alarming rate, with projections of a significant rise by the end of the century. This warming trend has far-reaching consequences impacting agriculture, the economy, and various aspects of human life (Zhang et al., 2024).

Climate change is already having a devastating impact on Saudi Arabia. Studies indicate that the Kingdom will face catastrophic climate consequences if it continues its current high-emissions trajectory. Without urgent action, agricultural droughts are projected to increase by 88% by 2050, heatwaves will become more frequent and prolonged by 4.242%, and the combined effects of sea-level rise, coastal erosion, and extreme weather events will disrupt the Saudi economy significantly, leading to an estimated 12.2% loss in GDP by 2050. However, the sooner Saudi Arabia adopts low-carbon policies, the less severe and manageable the climate impacts will become. Limiting global warming to 2 degrees Celsius would reduce the cost of climate impacts on Saudi Arabia to just 4.8% of its GDP by 2050 and 0.78% by 2100 G20 Climate Risk Atlas, 2021.

According to the Climate Transparency Report 2020, Saudi Arabia would need to reduce its emissions to below 389 MtCO2e by 2030 and to below 263 MtCO2e by 2050 to be within its emissions allowances under a 'fair-share' range compatible with global 1.5°C. The country's 2030 NDC range of 1,105-861 MtCO2e by 2030 is critically insufficient. All figures exclude land use emissions and are based on pre-COVID-19 projections (Climate Transparency Report, 2020). So Saudi Arabia aims to reduce, avoid, and remove greenhouse gas emissions by 278 million tons of CO_2 equivalent annually by 2030 and achieve net-zero emissions by 2060[(1)].

The Ecological Footprint, a concept developed in 1990 by Mathis Wackernagel and William Rees at the University of British Columbia, has evolved into a broader framework for assessing our impact on the planet. Crucially, the framework focuses on National Footprint and Biocapacity Accounts, which assess the ecological demands of nations against their available resources. Since 2019, these accounts have been managed by the Footprint Data Foundation (FoDaFo)[(2)], an independent organization, with ongoing support from York University[(3)]. This includes the Carbon Footprint, which measures the carbon dioxide emissions associated with the use of fossil fuels. In ecological footprint accounting, these quantities are converted into the biologically productive areas needed to absorb this carbon dioxide. The carbon footprint is added to the ecological footprint because it represents a competing use of biologically productive space, as increasing carbon dioxide concentrations in the atmosphere represents an accumulation of ecological debt. And other indicators such as (Built-up Land, Cropland, Grazing Land, Forest Land, Fishing Ground). Now widely adopted by scientists,

businesses, and governments, the Ecological Footprint helps track our resource consumption and guides sustainable development efforts[4].

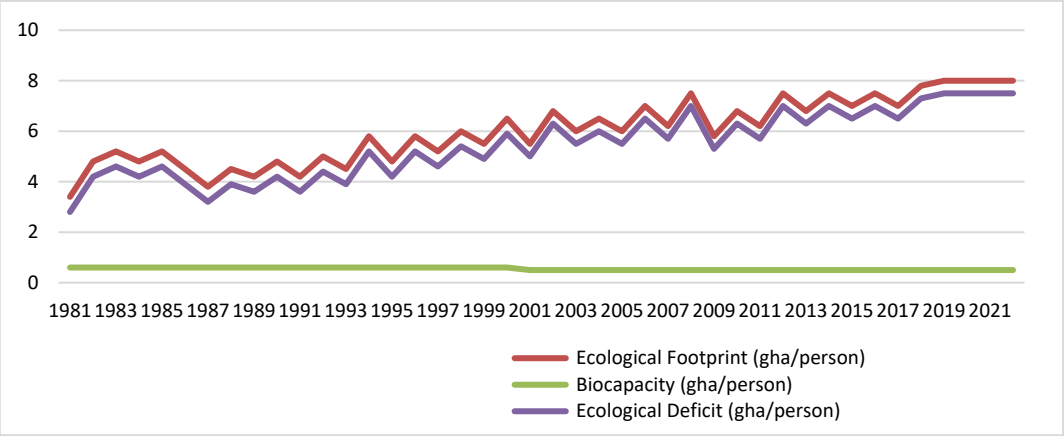
The Ecological Footprint measures our strain on the planet by calculating the demand for biologically productive land and water to support human activities. This includes the land needed to produce food, fiber, and absorb waste like carbon dioxide. When our demand exceeds the planet's ability to regenerate these resources, we create an ecological debt. Biocapacity, on the other hand, represents the planet's ability to replenish these resources. The Ecological Footprint is the sole metric that quantifies both our planet's available natural resources and our current consumption. It provides valuable insights for Countries To enhance sustainability and improve overall well-being. Local Leaders To optimize public project investments by considering their environmental impact. Also, Individuals To understand their personal ecological footprint and how their actions affect the planet[5].

Both the Ecological Footprint and biocapacity are measured in global hectares – standardized units reflecting global average productivity. This allows for comparisons between the Ecological Footprint of any city, state, or nation and its own biocapacity or that of the entire planet. When a population's Ecological Footprint surpasses its region's biocapacity, it creates a biocapacity deficit. This means the demand for resources like food (fruits, vegetables, meat, fish), timber, and the absorption of carbon dioxide exceeds what the local ecosystems can sustainably provide. To meet this demand, the region must resort to imports, deplete its own natural resources (overfishing, deforestation), or emit excessive carbon dioxide into the atmosphere. Conversely, a region with a biocapacity that exceeds its Ecological Footprint possesses a biocapacity reserve[6].

Saudi Arabia is the largest country in the Arabian Peninsula, with a coastline extending approximately 1,760 kilometers along the Red Sea and 560 kilometers along the Arabian Gulf, encompassing more than 1,000 islands and over 7,000 kilometers of total coastline. Most of the coastline is bordered by the Arabian Desert or mountains, particularly along the southern portion of the Red Sea coast. The coastline is a diverse mix of sandy and rocky shores, with extensive coastal plains in the Arabian Gulf region[7] and characterized by a desert climate with extremely hot days and cold nights, with the exception of the 'Asir region on the western coast, which has a semi-arid climate and a small area with a humid and mild temperature, with a long summer in the highlands north of Yemen.

In this country, the Ecological Footprint (EFP) indicator highlights the country’s environmental impact and resource consumption. According to recent studies, Saudi Arabia’s EFP is 5.7 global hectares per person, while its biocapacity is only 0.7 global hectares per person, indicating an ecological deficit of 5% in 2022. This means that Saudi Arabia’s demand for resources and services exceeds its own biocapacity, leading to environmental degradation.

Figure 1. *Saudi Arabia Ecological Footprint and Biocapacity from 1981 to 2022 (last 3 years are estimates)*



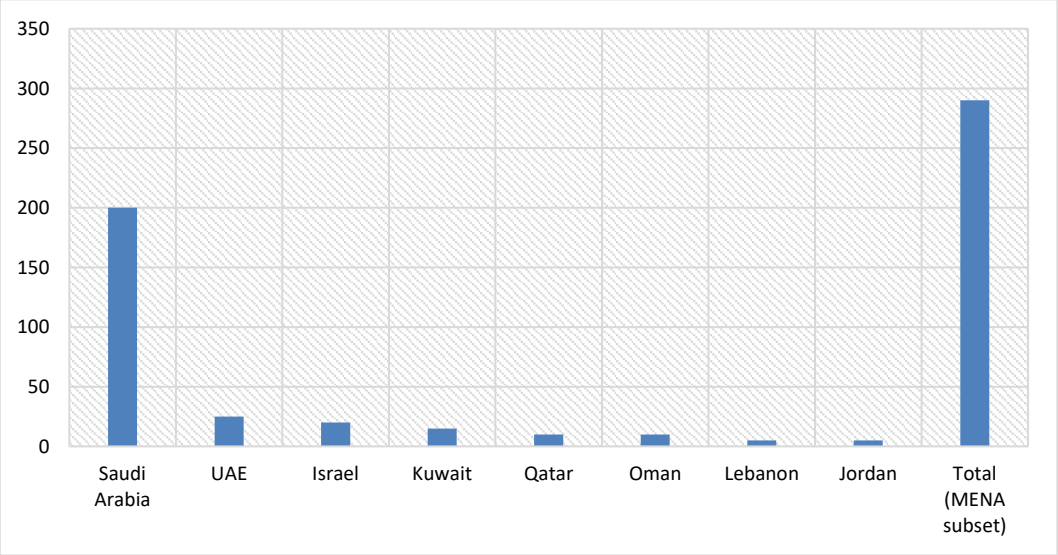
Source: National Footprint and Biocapacity Accounts2023 edition (Data Year 2019).

It is clear from the previous figure that Ecological Footprint Consumption Per Capita (EFConsPerCap) for Cropland recorded 0.827 hectares in 1981, while Biocapacity Per Capita (BiocapPerCap) for Cropland for the same year was 0.199 hectares. EFConsPerCap for Grazing Land recorded 0.353 gha, while BiocapPerCap for Grazing Land was 0.136 gha. EFConsPerCap for Forest Products was also 0.146 gha, while BiocapPerCap for Forest Products was 0.125 gha. This shows a decrease in the biocapacity of Cropland, Grazing Land, and Forest Products compared to the individual's ecological footprint for each. However, this decrease was within narrow limits and to a small extent, as carbon levels in the Saudi Arabian atmosphere were 1.42 in 1981, the lowest value. With the increase in carbon levels in the Saudi atmosphere during the period (1981-2022), the biocapacity of Cropland, Grazing Land, and Forest Products decreased, as it was estimated at 0.370, 0.093 and 0.049 gha, respectively, in 2022. This indicates a deterioration in the ability to regenerate resources that would preserve and support food security in the Kingdom as an inevitable result of the population increase, estimated at 36,408,800 people in 2022. Unsustainable human activities also contributed to the increase in carbon emissions, which reached 4.466 by 2022, which led to an increase in the ecological footprint of Cropland, Grazing Land, and Forest Products, which was estimated at 0.822, 0.192, and 0.151 gha, respectively, for the same year. This led to an increase in the overall ecological footprint for Saudi Arabia during 2022 to 5.7 gha per capita, while BiocapPerCap reached 0.697 gha, constituting a deficit of -5 gha. This danger threatens the Kingdom's resources and food security and affects the future of its development projects. Therefore, the Kingdom should move towards alternative strategies to reduce the ecological footprint and carbon emissions.

Studying the ecological footprint of Middle East and North African countries in 2022 revealed that Saudi Arabia has the highest resource demand, with a total resource demand of 209,186,031.9 gha. Its per capita resource demand was 5.75 gha. In contrast, Algeria's total resource demand was 99,818,395.88 gha, with a per capita demand of 2.22 gha, followed by the United Arab Emirates with approximately 82,277,817.42 gha and a per capita demand of 8.71 gha. Morocco followed with 57,882,655.39 gha and a per capita

demand of 1.55 gha. Jordan had the lowest resource demand among these countries, with 14,715,156.98 gha and a per capita demand of 1.3 gha. This contrasts with the per capita biocapacity, which represents the average amount of biologically productive land and water area available to each person within a given population to meet resource demands and absorb waste. It is a measure of the environment's capacity to regenerate the resources people use and absorb waste products.

Figure 2. *Ecological Footprint and Biocapacity for MENA in 2022*



Source: https://data.footprintnetwork.org/#/compareCountries?type=BCpc&cn=2022

While Oman emerged as the first country with about 1.8 gha in its inability to meet the local demand for resources by the population and achieve self-sufficiency and food security, followed by Qatar with 1.04 gha, then Kuwait with 0.81 gha, the Libyan Arab Jamahiriya with 0.77 gha, Tunisia with 0.72 gha, and then Saudi Arabia with about 0.7 gha, which illustrates the magnitude of the gap in the ability to achieve self-sufficiency of resources, as the per capita share of resource demand was 5.75 gha, and that there is a negative gap of -5 gha. Among the Arab countries that also have a negative gap in achieving adequacy of resources to meet the volume of local demand is Qatar, which is the first in terms of per capita demand for resources with about 13.13 gha, while the per capita biocapacity (the country's ability to meet individual demand) is 1.04 gha, which represents a very large gap that requires addressing to achieve self-sufficiency of food.

Several factors contribute to this situation:

- *Economic Development*: Saudi Arabia’s economy is heavily reliant on fossil fuels, which has led to significant greenhouse gas emissions. The country’s GDP was $1.11 trillion USD in 2022, with a high urbanization rate of 84%.
- *Greenhouse Gas Emissions*: Greenhouse gas emissions in Saudi Arabia rose from 466.494 million tons of CO2 equivalent per year (Mt CO2eq/yr) in 2005 to 810.512 Mt CO2eq/yr in 2022.

- *Renewable Energy*: Studies have shown that increasing renewable energy consumption can improve environmental quality by reducing the ecological footprint. However, the current reliance on fossil fuels continues to contribute to environmental degradation.
- *Policy Implications*: Policymakers are encouraged to implement measures that reduce the ecological footprint and improve environmental quality with renewable energy and sustainable practices.

These factors highlight the need for sustainable development strategies to address the ecological footprint in Saudi Arabia. In this context, the Saudi government has adopted ambitious policies to transition towards a more sustainable and resilient economy. A key initiative is the Vision 2030 program, which prioritizes economic diversification, renewable energy expansion, and environmental conservation. The country is heavily investing in solar and wind energy projects, such as the NEOM city project and Sakaka Solar Plant, to reduce dependence on fossil fuels. Additionally, the Saudi Green Initiative aims to combat desertification and lower carbon emissions by planting 10 billion trees and expanding protected natural areas. To meet international climate commitments, Saudi Arabia has pledged to achieve net-zero carbon emissions by 2060, aligning with global efforts to mitigate climate change.

Furthermore, policy interventions focus on enhancing food security and optimizing natural resource management. Given its high dependence on food imports and limited freshwater resources, Saudi Arabia is promoting innovative agricultural practices, such as vertical farming, hydroponics, and seawater desalination for irrigation. Investments in advanced water management technologies and policies encouraging sustainable consumption patterns are also being implemented to reduce the ecological footprint. The government is actively fostering international partnerships to secure food supply chains and develop sustainable agricultural projects abroad. These integrated strategies aim to ensure long-term economic stability, environmental protection, and food security while minimizing the country's ecological deficit.

Given the above, the paper is structured as follows: After introduction, Section 2 provides a literature review; Section 3 presents the data and the empirical model; Section 4 outlines the methodology; Section 5 covers the results and discussion, and Section 6 concludes the paper.

II. Literature Review

Saudi Arabia's water security has been the subject of extensive international research, with numerous studies exploring the link between climate change and water scarcity in the country. For instance, studies by (John et al., 2024), (DeNicola et al., 2015), and (Almazroui et al., 2017:pp11–23) have delved into this issue. Similarly, a substantial body of research examines the broader impacts of climate change on Saudi Arabia. In contrast, the focus on food security in Saudi Arabia within the context of climate change has been relatively limited. While studies by (Baig et al., 2019:pp1743–1752), (Fiaz et al., 2018:pp365–375), (Kajenthira Grindle et al.,2015:pp 67–78), and (Haque & Khan,

2020:pp1-18) have touched on this topic, the depth and breadth of research in this area falls short of that on water security. In the following sections, we will review these studies and explore additional literature that examines the relationship between climate change and food security in other countries.

Numerous studies have demonstrated that climate change has far-reaching and multifaceted impacts, affecting various sectors, including agriculture, energy, the economy, finance, food security society, politics, and human health (John et al., 2024) (Goli et al., 2024) ; (Wang et al., 2024). Climate change is affecting low-income countries, emerging markets, and advanced economies (Toiba et al., 2024).

(Ceesay & Ben Omar Ndiaye, 2022: pp. 1-11) study empirically examined the causal relationship between climate change, rainfall variability, food security, economic growth, population growth, and the agricultural sector. Utilizing data from the World Development Indicators (WDI) spanning 1971-2020 in the Gambia, the study employed a suite of econometric techniques, including Vector Autoregression (VAR), Granger causality, Autoregressive Distributed Lag (ARDL), and Error Correction Model (ECM). The findings revealed a strong positive correlation between food security growth and the agricultural sector, while a negative correlation was observed between food security and rainfall variability. Furthermore, population growth exhibited a significant negative short-term impact on food security, though this long-term impact was found to be insignificant. Based on these results, the study recommends that the Gambian government prioritize initiatives such as afforestation to enhance agriculture and the environment, food security intervention programs, poverty reduction efforts, the development of adaptive capacity indicators, equitable access to quality education, systemic changes to improve governance, institutions, and inclusive economic growth, and consideration of export-oriented economic strategies.

Previous studies by(Khurshid & Abid, 2024) underscore the significant threat of climate change to food security, primarily through its impact on crop yields and food availability. Short-term fluctuations induced by climate change and global politics can disrupt the stability of entire food systems. Conducted in Pakistan using a time series spanning from 1981 to 2021, employed the Nonlinear Autoregressive Distributed Lag (NARDL) model to examine the asymmetric effects of political globalization (proxied by political globalization) and environmental change (proxied by CO2 and mean temperature) on food security. The findings indicated an asymmetric impact of mean temperature (MT), CO2 emissions, and political globalization (POLG) on food security. While CO2_POS, CO2_NEG, MT_POS, and MT_NEG exhibited a positive relationship with food security, POLG_POS and POLG_NEG displayed a negative correlation.

While (Habtie et al., 2024:pp 1-20) study conducted in Tigray, Ethiopia, over three periods (1983-2015, 2011-2014, and 2016-2019) using data from the Ethiopia Rural Socioeconomic Survey (ERSS), revealed that rising temperatures have led to an 85.53% increase in drought frequency and threaten the welfare of the population by 23%. Moreover, the study concluded that climate change is a tangible reality and a significant

risk in Tigray, posing a threat to the lives and livelihoods of farming communities. The study recommends enhancing the adaptive capacity of farm households through improved livelihood options, fostering cooperation, developing irrigation schemes, and increasing access to weather and climate information.

The study by (Meierrieks & Stadelmann, 2024) established a negative correlation between rising temperatures and regional economic development. Analyzing over 1,500 regions across 152 countries from 1990 to 2017, they employed panel data and a long-difference approach. The findings indicate that elevated temperatures exert a significant long-term adverse effect on regional per capita income, reaching a 1% significance level. This detrimental impact is attributed to the negative consequences of higher temperatures on labor productivity and human capital development, which ultimately obstruct economic growth.

Furthermore, (John et al.,2024) study focuses on testing the causal relationship between climate change and food security in the Economic Community of West African States (ECOWAS) region over the period from 1986 to 2022. Departing from previous studies, this research incorporates the Dumitrescu-Hurlin Panel Causality test, Pooled Mean Group (PMG), Common Correlated Effect Mean Group (CCEMG), Augmented Mean Group (AMG), and Cross-Sectional Augmented Autoregressive Distributed Lag (CS-ARDL) techniques to analyze the complex relationship between climate change and food security in the ECOWAS region. Unlike prior empirical studies, the findings reveal a robust mutual influence between climate change and food security in the ECOWAS region. The study relied on six key variables: food security (FS), climate change (EFP), agricultural value added (AVA), cropland area (CLA), rainfall (RF), drought (ASI), and population growth (POP). Results indicated a positive impact of climate change on food security, facilitated by increased cropland area and population growth. However, drought incidence and erratic rainfall between July and September remained a significant concern in the region. While the conversion of forests and natural habitats into cropland in the sub-region can lead to heightened carbon emissions and reduced ecosystem services, policy recommendations advocate ECOWAS policymakers to carefully balance the benefits of food security through sustainable practices and environmental considerations to ensure long-term food security benefits.

As (Haque & Khan ,2020:pp 1-18) study aimed to investigate the impact of climate change trends in temperature and rainfall on major crop production in Saudi Arabia over the period 1967-2016. By employing variables such as rainfall, temperature, and major crop yields in the Kingdom, the study establishes an empirical association between crop yields and climatic variables using a fixed-effects regression framework. This approach enables the capture of time-invariant factors and farmers' independent adaptation strategies in response to year-to-year variations in precipitation and temperature. The findings reveal a substantial increase of 1.9 degrees Celsius in the average temperature over the past 50 years, with the most significant rise occurring in the summer months. However, no considerable change in rainfall was observed. Results indicate that a one-degree Celsius increase in temperature

leads to a 7-25% reduction in crop yields. While rainfall exhibits a positive impact on all crops, it is insufficient to offset the adverse effects of temperature. Consequently, the Kingdom must develop a roadmap for future food, water, and nutritional security to mitigate the potential impacts of global shocks arising from climate change or geopolitical instability. (ARDL)

Like previous studies, (Rahman et al., 2022:pp1-19) confirmed the existence of a causal relationship between climate change and food security in Saudi Arabia. The primary objective of this study was to investigate the causal relationship between climate change and food security in Saudi Arabia. Given the significant impact of climate variability and extreme weather events on the country's vulnerable food system, and the unique challenges faced by Saudi Arabia compared to other arid regions, the study conducted a causality analysis. This analysis examined various driving factors, including temperature (tem), greenhouse gas emissions (GHG), population (pop), and gross domestic product (GDP), that contributed to vulnerabilities in the food system from 1990-2019. The results of the long-run causality test revealed a positive causal relationship between GDP and food demand, indicating that as GDP increases, too will food demand in the long run. Additionally, the study found that Saudi Arabia's GDP growth and population growth are contributing factors to the increase in total GHG emissions. Despite the Kingdom's efforts to combat climate change, there remains ample opportunity to implement strategies that ensure the nation's food security.

Furthermore, (Baig et al., 2019:pp1743–1752) study was to investigate the issue of food waste in Saudi Arabia, a pressing concern for sustainability. The research centered on a comprehensive review of both gray and scientific literature published in English and Arabic on food waste within the Kingdom. Information was gathered from various sources, including Web of Knowledge, online resources, and databases accessible through King Saud University. The study delved into the social, cultural, economic, and environmental impacts of food waste. Given the abundant availability of subsidized food in Saudi Arabia, residents often take food for granted. A recent survey revealed that approximately 78% of purchased food is discarded weekly, highlighting the severity of the issue. Despite limited arable land and scarce water resources, Saudi Arabia, ranking among the top food-wasting countries with an average of 427 kg of food wasted per capita annually, heavily relies on imports and subsidized food to meet its growing population's needs.

In addition, the study by (Fiaz et al., 2018:pp365–375) highlighted the critical need for food security in Saudi Arabia, given the inadequacy of domestic production and the heavy reliance on imported grains and red meat. With projections indicating that Saudi Arabia will be entirely dependent on imports by 2050, the study emphasizes the importance of adopting advanced technologies such as promoting traditional crops, hydroponics, greenhouse farming, seawater harvesting, and investing in bio-salinity research and rainwater harvesting. Moreover, the study underscores the need to raise awareness among the farming community to implement guidelines and meet the country's dietary needs.

As highlighted in the study by (Kajenthira Grindle et al., 2015: pp 67–78), the trade of 'virtual water' through agricultural commodities and direct investment in overseas food

production has emerged as an alternative strategy. This approach holds significant potential for enhancing the sustainability of global food production by optimizing the utilization of water, energy, and labor resources. By focusing on overseas food production to meet domestic demand, Saudi Arabia aims to alleviate water scarcity and ensure food security. However, such a shift could have profound implications for local water and energy consumption as well as labor markets while also presenting opportunities for achieving greater sustainability.

A review of the existing literature has revealed several research gaps. What distinguishes this study is threefold, namely:

1. *A methodological gap*: It employs the ARDL model to simulate the effects of climate change on food security and economic growth in Saudi Arabia. This methodological approach enhances the robustness of the research findings.
2. *A variable gap*: The study introduces novel variables not previously explored in the context of Saudi Arabia, including food security (FS), Ecological Footprint (EFP), Biocapacity Per Capita (BPC) agricultural value added (AVA), rainfall (RF), and population growth (POP).
3. *A temporal gap*: The study focuses on the contemporary period to assess the recent impacts of climate change on food security and economic growth in Saudi Arabia. within (1981- 2022).

III. Data and empirical Model

The study's main objective is to explore how climate change affects food security, economic growth, and growth rate of agriculture sector in Saudi Arabia.

The following models are written as:

$$EFP_t = f(FS_t, RF_t, POP_t, AGR_t, GDPC_t) \quad (1)$$

$$RF_t = f(FS_t, POP_t, AGR_t, GDPC_t) \quad (2)$$

$$FS_t = f(EFP_t, POP_t, AGR_t, GDPC_t) \quad (3)$$

$$GDPC_t = f(RF_t, POP_t, AGR_t, FS_t) \quad (4)$$

In these models, EFP represents the environmental footprint, which measures the pressure exerted on the environment due to economic and social activities. This accounts for all harvest and emission within the country from cropland, grazing land, forest land, marine/inland fishing footprint, built-up land, and anthropogenic emission. FS denotes food security, capturing the availability and accessibility of food in the Saudi Arabic. RF stands for rainfall, which influences agricultural output and water resources. POP represents the total population, reflecting the size of the human resource base and its potential impact on resource consumption and environmental stress. AGR refers to the agricultural sector, which is crucial for food production and rural livelihoods. GDPC represents GDP per capita, used as a proxy for economic well-being and overall productivity.

In the table below, we presented a definition of each variable, along with their respective data sources.

Table 1. *The definition of each variable*

Name of Variable	Source	Comment
GDP per capital (GDPC)	WDI	GDP per capita
Agriculture (AGR)	WDI	Agriculture value added of $
Food Security (FS)	WDI	Food production (food security proxy)
Rainfall (RF)	WB	Average annual rainfall (climate change proxy)
Population (POP)	WDI	Population
GDP current (GDP)	WDI	GDP current $
ecological footprint (EFP)	Footprintnetwork	Measure using the Global hectares (gha) per capita (climate change proxy)

Source: the authors.

The model mentioned above can be written as follows:

$$ln(EFP_t) = \beta_0 + \beta_1 ln(FS_t) + \beta_2 ln(RF_t) + \beta_3 ln(POP_t) + \beta_4 ln(AGR_t) + + \beta_5 ln(GDPC_t) + \epsilon_t \quad (3)$$

$$ln(RF_t) = \gamma_0 + \gamma_1 ln(FS_t) + \gamma_2 ln(POP_t) + \gamma_3 ln(AGR_t) + +\gamma_4 ln(GDPC_t) + \nu_t \quad (4)$$

$$ln(FS_t) = \omega_0 + \omega_1 ln(EFP_t) + \omega_2 ln(POP_t) + \omega_3 ln(AGR_t) + +\omega_4 ln(GDPC_t) + \theta_t \quad (5)$$

$$\ln(GDPC_t) = \varphi_0 + \varphi_1 ln(FS_t) + \varphi_2 ln(POP_t) + \varphi_3 ln(AGR_t) + + \varphi_4 ln(RF_t) + \rho_t \quad (6)$$

where,

$\varepsilon_t, \nu_t, \theta_t, \rho_t$ are the error and $\beta_0, \gamma_0, \varphi_0, \omega_0$ displays the constant term,

$\alpha_1, \alpha_2, \alpha_3, \alpha4, \alpha_4, \gamma_1, \gamma_2, \gamma_3, \gamma_4$, $\omega_1, \omega_2, \omega_3, \omega_4, \varphi_1, \varphi_2, \varphi_3, \varphi_4, \varphi_4$ are the coefficients.

All the variables are used in log form.

Table 2 and 3 presents summary statistics and correlation between the variables, while Figure 3 displays the plots of these variables.

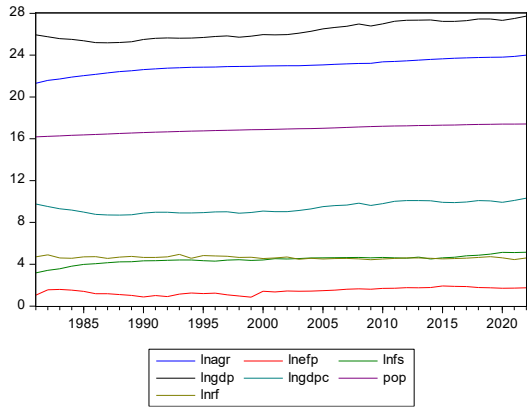
Based on the summary statistics, it is evident that all variables follow a normal distribution as the Jarque-Bera probability is higher than 1% and 5%.

Table 2. *Summary statistics*

	LNAGR	LNEFP	LNFS	LNGDPC	LNPOP	LNRF
Mean	22.96307	1.433541	4.442042	9.412571	16.90321	4.631849
Median	22.97490	1.459892	4.511517	9.302554	16.92247	4.600910
Maximum	24.00644	1.924697	5.151324	10.32377	17.41032	4.950885
Minimum	21.30603	0.857821	3.178054	8.699219	16.18372	4.434500
Std. Dev.	0.645943	0.310588	0.409656	0.502511	0.368582	0.113420
Skewness	-0.612153	-0.291545	-1.001790	0.190428	-0.293524	0.754734
Kurtosis	2.975042	1.853249	4.654409	1.516536	1.948677	3.485467
Jarque-Bera	2.624208	2.896308	11.81495	4.105006	2.537333	4.399802
Probability	**0.269253**	**0.235004**	**0.002719**	**0.128413**	**0.281206**	**0.110814**
Sum	964.4491	60.20872	186.5658	395.3280	709.9349	194.5377
Sum Sq. Dev.	17.10695	3.955055	6.880537	10.35320	5.569971	0.527428
Observations	42	42	42	42	42	42

Source: the author.

Figure 3. *Plot of variables*



Source: the authors.

Table 3. *Correlation matrix*

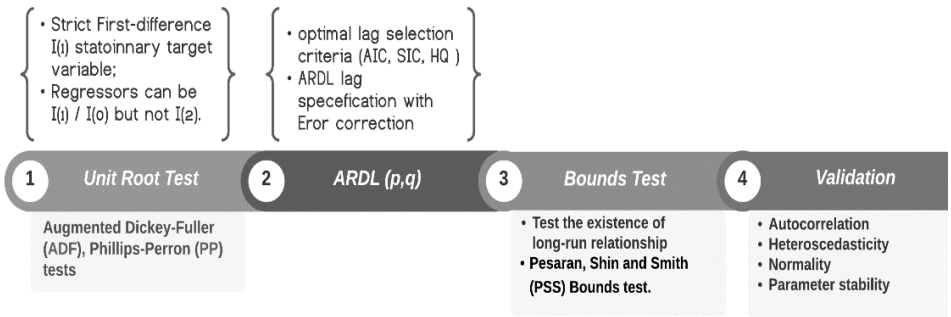
	LNAGR	LNEFP	LNFS	LNGDPC	LNPOP	LNRF
LNAGR	1.000000					
LNEFP	0.586089	1.000000				
LNFS	0.956572	0.464855	1.000000			
LNGDPC	0.629895	0.843941	0.481742	1.000000		
LNPOP	0.978761	0.687574	0.912252	0.739532	1.000000	
LNRF	-0.423307	-0.485366	-0.424263	-0.416054	-0.494371	1.000000

Source: the authors.

IV. Methodology: the ARDL model approach

Figure below shows stages for modeling the effects of climate change on Food security and economic growth. In the first step, ADF and PP tests are utilized to check variable stationarity and identify integration order. In the second step, we estimated the ARDL model when all variables integrate into I (0) and I (1) to determine short and long-run relationships between variables. The third step, we employed the PSS bound test to ascertain the presence of long-term cointegration among the variables. We employ stability tests to validate the ARDL model during the fourth step.

Figure 4. *Modeling steps*



Source: the authors.

Numerous cointegration techniques exist for analyzing the long-term relationship between macroeconomic variables. (Granger, 1981; Engle & Granger, 1987; Johansen & Juselius, 1990; Johansen, 1995)

Using the cointegration technique developed by Pesaran & Shin, (1995) and Pesaran et al., (2001) has several advantages compared to traditional techniques. First, this approach is suitable for a small sample size. The current study covers 42 annual observations, making it a better fit for this case. In contrast, traditional cointegration approaches require a large sample size and are not valid for a small sample (Narayan & Narayan, 2005). Second, the traditional methods require solving many equations, whereas this approach is easy to use and interpret.

From equations (3), (4), (5), and (6), the ARDL models used in this study can be expressed as:

$$\begin{aligned}\Delta ln(EFP_t) = \ & \alpha_0 + \sum_{\{i=1\}}^{p} \tau_i \Delta ln\left(EFP_{\{t-1\}}\right) + \sum_{\{i=1\}}^{p} \beta_i \Delta ln\left(FS_{\{t-1\}}\right) \\ & + \sum_{\{i=1\}}^{p} \theta_i \Delta ln\left(RF_{\{t-1\}}\right) + \sum_{\{i=1\}}^{p} \vartheta_i \Delta ln\left(POP_{\{t-1\}}\right) \\ & + \sum_{\{i=1\}}^{p} \delta_i \Delta ln\left(AGR_{\{t-1\}}\right) + \sum_{\{i=1\}}^{p} \xi_i \Delta ln\left(GDPC_{\{t-1\}}\right) \\ & + \gamma_{EFP} ln\left(EFP_{\{t-1\}}\right) + \gamma_{FS} ln\left(FS_{\{t-1\}}\right) + \gamma_{RF} ln\left(RF_{\{t-1\}}\right) \\ & + \gamma_{POP} ln\left(POP_{\{t-1\}}\right) + \gamma_{AGR} ln\left(AGR_{\{t-1\}}\right) + \gamma_{GDPC} ln\left(GDPC_{\{t-1\}}\right) \\ & + \epsilon_t \end{aligned} \quad (7)$$

Where:

$\tau i, \beta_i, \theta_i, \vartheta_i, \delta_i, \xi_i$ represent short-run coefficients for each respective lagged differenced variable.

$\gamma_{EFP}, \gamma_{FS}, \gamma_{RF}, \gamma_{POP}, \gamma_{AGR}, \gamma_{GDPC}$ are the long-run coefficients for the levels of each variable.

ϵ_t is the error term.

$$\begin{aligned}\Delta ln(RF_t) = \ & \alpha'_0 + \sum_{\{i=1\}}^{p} \tau'_i \Delta ln\left(RF_{\{t-1\}}\right) + \sum_{\{i=1\}}^{p} \beta'_i \Delta ln\left(FS_{\{t-1\}}\right) \\ & + \sum_{\{i=1\}}^{p} \vartheta'_i \Delta ln\left(POP_{\{t-1\}}\right) + \sum_{\{i=1\}}^{p} \delta'_i \Delta ln\left(AGR_{\{t-1\}}\right) \\ & + \sum_{\{i=1\}}^{p} \xi'_i \Delta ln\left(GDPC_{\{t-1\}}\right) + \gamma'_{RF} ln\left(RF_{\{t-1\}}\right) + \gamma'_{FS} ln\left(FS_{\{t-1\}}\right) \\ & + \gamma'_{POP} ln\left(POP_{\{t-1\}}\right) + \gamma'_{AGR} ln\left(AGR_{\{t-1\}}\right) + \gamma'_{GDPC} ln\left(GDPC_{\{t-1\}}\right) \\ & + \nu_t \end{aligned} \quad (8)$$

Where:

$\tau'_i, \beta'_i, \vartheta'_i, \delta'_i, \xi'_i$ are the short-run coefficients for the differenced lagged variables.

$\gamma'_{FS}, \gamma'_{POP}, \gamma'_{AGR}, \gamma'_{GDPC}$ are the long-run coefficients for the levels of each variable.

ν_t is the error term.

$$\begin{aligned}\Delta ln(FS_t) = \ & \alpha''_0 + \sum_{\{i=1\}}^{p} \tau''_i \Delta ln\left(EFP_{\{t-1\}}\right) + \sum_{\{i=1\}}^{p} \beta''_i \Delta ln\left(FS_{\{t-1\}}\right) \\ & + \sum_{\{i=1\}}^{p} \vartheta''_i \Delta ln\left(POP_{\{t-1\}}\right) + \sum_{\{i=1\}}^{p} \delta''_i \Delta ln\left(AGR_{\{t-1\}}\right) \\ & + \sum_{\{i=1\}}^{p} \xi''_i \Delta ln\left(GDPC_{\{t-1\}}\right) + \gamma''_{EFP} ln\left(EFP_{\{t-1\}}\right) + \gamma''_{FS} ln\left(FS_{\{t-1\}}\right) \\ & + \gamma''_{POP} ln\left(POP_{\{t-1\}}\right) + \gamma''_{AGR} ln\left(AGR_{\{t-1\}}\right) \\ & + \gamma''_{GDPC} ln\left(GDPC_{\{t-1\}}\right) + \nu'_t \end{aligned} \quad (9)$$

Where:

$\tau''_i, \beta''_i, \vartheta''_i, \delta''_i, \xi''_i$ are the short-run coefficients for the differenced lagged variables.

$\gamma''_{FS}, \gamma''_{POP}, \gamma''_{AGR}, \gamma''_{GDPC}$ are the long-run coefficients for the levels of each variable.

ν'_t is the error term.

$$\begin{aligned}\Delta ln(GDPC_t) = \ & \alpha_0 + \sum_{\{i=1\}}^{p} \tau'''_i \Delta ln\left(GDPC_{\{t-1\}}\right) + \sum_{\{i=1\}}^{p} \beta'''_i \Delta ln\left(FS_{\{t-1\}}\right) \\ & + \sum_{\{i=1\}}^{p} \vartheta'''_i \Delta ln\left(POP_{\{t-1\}}\right) + \sum_{\{i=1\}}^{p} \delta'''_i \Delta ln\left(AGR_{\{t-1\}}\right) \\ & + \sum_{\{i=1\}}^{p} \xi'''_i \Delta ln\left(RF_{\{t-1\}}\right) + \gamma'''_{GDPC} ln\left(GDPC_{\{t-1\}}\right) \\ & + \gamma'''_{FS} ln\left(FS_{\{t-1\}}\right) + \gamma'''_{POP} ln\left(POP_{\{t-1\}}\right) + \gamma'''_{AGR} ln\left(AGR_{\{t-1\}}\right) \\ & + \gamma'''_{RF} ln\left(RF_{\{t-1\}}\right) + \nu''_t \end{aligned} \quad (10)$$

Where:

$\tau'''_i, \beta'''_i, \vartheta'''_i, \delta'''_i, \xi'''_i$ are the short-run coefficients for the differenced lagged variables.

$\gamma'''_{GDPC}, \gamma'''_{POP}, \gamma'''_{AGR}, \gamma'''_{RF}$ are the long-run coefficients for the levels of each variable.

ν''_t is the error term.

V. Results and Discussion

5.1. Unit Root Test

To determine integration order and yield comprehensive results, unit root tests, such as the Phillips-Perron (PP) and Augmented Dickey-Fuller (ADF) tests (Dickey & Fuller, 1981; Perron, 1989), are employed to assess parameter characteristics.

The unit root test findings in Table 4 indicate that the ARDL model can be applied to the analyzed variables—the stationarity and integration order of variables at I(0) and I(1).

Table 4. *Unit root tests*

Variable	Level.PP	$\Delta_{,PP}$	Level.ADF	$\Delta_{,ADF}$	Remark
LNAGR	-4.901364***	-3.421951***	-2.129217	-3.315073***	I(0)
LNEFP	0.591574	-7.694866***	0.386954	-7.651270***	I(1)
LNFS	-4.193823***	-5.280971***	-4.666199***	-5.266462***	I(1)
LNGDPC	-4.008823***	-4.621102***	-4.036780***	-4.623999***	I(0)
LNPOP	-5.192928***	-1.679673	0.804364	-1.717137**	I(0)
LNRF	-4.306283***	-15.35334***	-4.289945***	-10.61128***	I(0)

Notes: Where Level.PP and PP denote the level and first-difference of Phillips-Perron unit root test; Level.ADF and ADF denote the level and first-difference of augmented-Dickey Fuller unit root test;
*** denotes rejection of the null hypothesis of no unit root at 1% significance level.
** denotes rejection of the null hypothesis of no unit root at 5% significance level.
Source: the authors.

5.2. Estimation of ARDL Model

To estimate the ARDL model accurately, choosing the most suitable lag is crucial. This selection is guided by several criteria, including the Akaike Information Criterion (AIC), Hannan-Quinn Information Criterion (HQIC), and Schwarz's Bayesian Information Criterion (SBIC). These criteria serve as essential tools in the modeling process, aiding in determining the optimal lag.

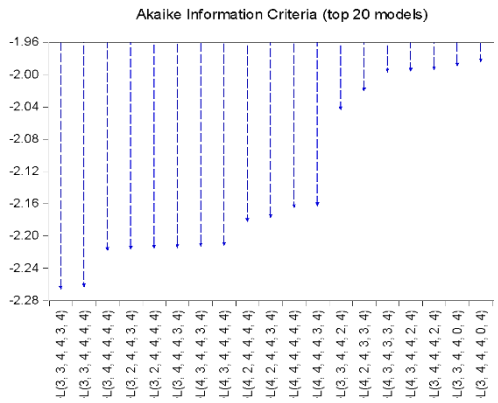
In our case, we selected Schwarz's Bayesian Information Criterion (SBIC) for model selection (Figure **).

Co-integration

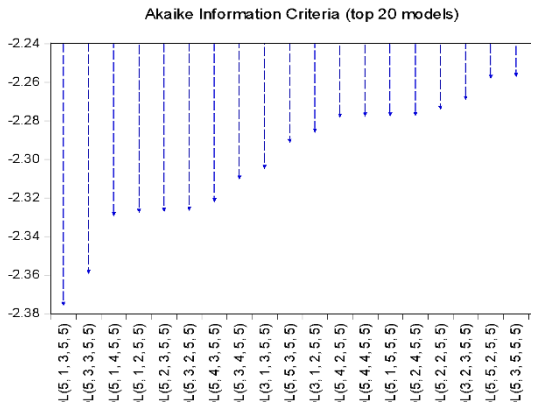
Table 5 presents the results of the co-integration test between variables using Bounds test. The results indicate that the F-statistic, exceeds the critical values at 1%, 5%, and 10%. Consequently, the null hypothesis is rejected. This conclusion suggests a long-term relationship between variables in both models.

Figure 5. *Model selection method: Schwarz criterion (SIC)*

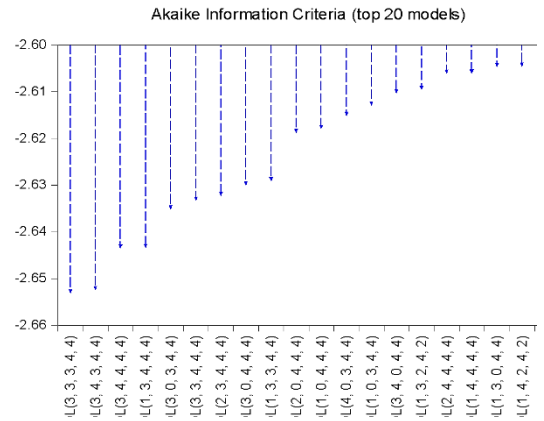
Model 1



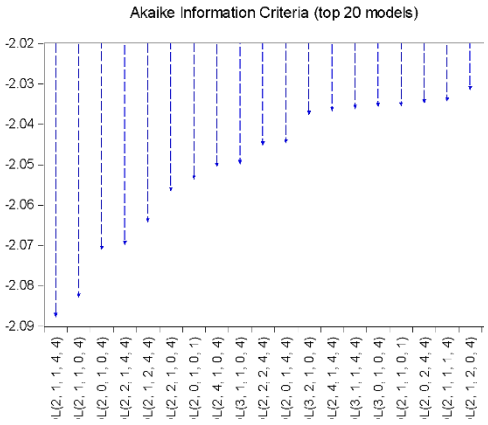
Model 2



Model 3



Model 4



Source: the authors.

Table 5. *Pesaran, Shin, and Smith Bounds Testing F-Bounds Test*

	Test statistic	Lower Bound I (0)	Upper Bound I (1)	Remark
F.Statistic (model 1)	9.159514	2.734	3.92	long-run relationship
F.Statistic (model 2)	4.600063	2.893	4	long-run relationship
F.Statistic (model 3)	2.012358	3.548	4.803	No long-run relationship
F.Statistic (model 4)	6.357034	2.56	4.913	long-run relationship

Source: the authors.

Short-Run and Long-Run Coefficient

After confirming the existence of a co-integration relationship through F statistics in the models 1,2 and 4, we can now estimate long-run and short-run elasticity. Table 6 estimates a short-run equation among the variables in each model:

Table 6. *Short-run estimation equation*

Model 1 Dependent Variable: D(LNEFP)					Model 2 Dependent Variable: D(LNRF)				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**Variable**	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
D(LNEFP(-1))	0.411488	0.110191	3.734304	0.0033	D(LNRF(-1))	1.563065	0.442820	3.529795	0.0037
D(LNEFP(-2))	0.527671	0.105489	5.002161	0.0004	D(LNRF(-2))	0.954821	0.337824	2.826382	0.0143
D(LNFS)	0.048351	0.183785	0.263082	0.7973	D(LNRF(-3))	0.416560	0.220674	1.887668	0.0816
D(LNFS(-1))	-0.802556	0.172006	-4.665854	0.0007	D(LNRF(-4))	0.269081	0.128372	2.096105	0.0562
D(LNFS(-2))	-0.345868	0.172408	-2.006105	0.0701	D(LNFS)	-0.664803	0.201770	-3.294854	0.0058
D(LNRF)	-0.345084	0.152137	-2.268246	0.0444	D(POP)	-14.10682	3.197168	-4.412287	0.0007
D(LNRF(-1))	2.612407	0.350441	7.454623	0.0000	D(POP(-1))	18.92533	5.019198	3.770589	0.0023
D(LNRF(-2))	1.536794	0.263663	5.828638	0.0001	D(POP(-2))	-5.876945	2.976703	-1.974314	0.0700
D(LNRF(-3))	0.604902	0.137463	4.400484	0.0011	D(LNAGR)	0.156295	0.568573	0.274890	0.7877
D(POP)	-7.250597	3.554743	-2.039696	0.0661	D(LNAGR(-1))	-2.390675	0.877673	-2.723880	0.0174
D(POP(-1))	4.071553	6.475937	0.628720	0.5424	D(LNAGR(-2))	-2.392763	0.796707	-3.003316	0.0102
D(POP(-2))	0.014486	6.679600	0.002169	0.9983	D(LNAGR(-3))	-1.795026	0.823096	-2.180822	0.0482
D(POP(-3))	-13.30083	3.915733	-3.396766	0.0060	D(LNAGR(-4))	-1.449324	0.463011	-3.130214	0.0080
D(LNAGR)	-0.793987	0.603193	-1.316307	0.2148	D(LNGDPC)	0.093283	0.120329	0.775234	0.4521
D(LNAGR(-1))	-1.729104	0.790214	-2.188146	0.0511	D(LNGDPC(-1))	-0.482121	0.168258	-2.865374	0.0133
D(LNAGR(-2))	-2.558811	0.779116	-3.284249	0.0073	D(LNGDPC(-2))	-0.412238	0.192704	-2.139230	0.0520
D(LNGDPC)	0.328651	0.112959	2.909481	0.0142	D(LNGDPC(-3))	-0.438250	0.158745	-2.760709	0.0162
D(LNGDPC(-1))	-1.115440	0.202422	-5.510454	0.0002	D(LNGDPC(-4))	-0.523632	0.139891	-3.743145	0.0025
D(LNGDPC(-2))	-0.936528	0.165498	-5.658834	0.0001	CointEq(-1)*	**-3.212347**	**0.519637**	**-6.181902**	**0.0000**
D(LNGDPC(-3))	-0.735599	0.176354	-4.171145	0.0016					
CointEq(-1)*	**-1.469580**	**0.147632**	**-9.954360**	**0.0000**					
R2	**0.910828**				R^2	**0.892911**			
Adjusted R2	**0.805921**				Adjusted R^2	**0.785822**			
DW- stat	2.498903				DW- stat	2.587920			
Model 3: Dependent Variable: D(LNFS)					**Model 4: Dependent Variable: D(LNGDPC)**				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**Variable**	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
D(LNFS(-1))	-0.056738	0.148413	-0.382300	0.7070	D(LNGDPC(-1))	0.618254	0.126550	4.885473	0.0001
D(LNEFP)	0.011593	0.079565	0.145703	0.8859	D(LNRF)	0.255756	0.104055	2.457895	0.0228
D(LNEFP(-1))	0.003965	0.079558	0.049838	0.9608	D(LNFS)	-0.625606	0.193321	-3.236096	0.0040
D(LNEFP(-2))	-0.184994	0.083583	-2.213306	0.0408	D(POP)	4.556732	3.231835	1.409952	0.1732
D(LNRF)	0.007537	0.104915	0.071841	0.9436	D(POP(-1))	-9.392151	5.948699	-1.578858	0.1293
D(LNRF(-1))	0.426742	0.135824	3.141878	0.0059	D(POP(-2))	13.54038	6.491553	2.085846	0.0494
D(LNRF(-2))	0.263117	0.100755	2.611459	0.0182	D(POP(-3))	-10.77322	3.833017	-2.810636	0.0105
D(LNAGR)	0.404642	0.440239	0.919142	0.3709	D(LNAGR)	2.788585	0.513797	5.427402	0.0000
D(LNAGR(-1))	-0.128628	0.652139	-0.197241	0.8460	D(LNAGR(-1))	0.077290	0.553490	0.139641	0.8903
D(LNAGR(-2))	-1.645163	0.537318	-3.061807	0.0071	D(LNAGR(-2))	0.504066	0.479159	1.051982	0.3048
D(LNAGR(-3))	1.310865	0.307946	4.256808	0.0005	D(LNAGR(-3))	1.311171	0.477097	2.748228	0.0120
D(LNGDPC)	-0.230087	0.104461	-2.202617	0.0417	CointEq(-1)*	**-0.802117**	**0.116723**	**-6.871949**	**0.0000**
D(LNGDPC(-1))	-0.008572	0.111699	-0.076739	0.9397					
D(LNGDPC(-2))	0.187832	0.128095	1.466352	0.1608					
D(LNGDPC(-3))	-0.301593	0.110320	-2.733814	0.0141					
CointEq(-1)*	**-0.093477**	**0.023398**	**-3.995152**	**0.0009**					
R^2	**0.696025**				R^2	**0.799597**			
Adjusted R^2	**0.464426**				Adjusted R^2	**0.714810**			
DW- stat	2.153334				DW- stat	2.057270			

Source: the authors.

After assessing short-term elasticity, the next step is to examine the findings regarding long-term elasticity. The results for long-term elasticity are displayed in Table 7 below:

Table 7. *Long-run estimation equation*

Model 1 Dependent Variable: LNEFP					Model 2 Dependent Variable: LNRF				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**Variable**	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
LNFS	0.280184	0.190478	1.470953	0.1693	LNFS	-0.037091	0.045990	-0.806508	0.4345
LNRF	-2.239886	0.723243	-3.097003	0.0102	POP	-1.859097	0.214146	-8.681455	0.0000
POP	-2.055107	1.088852	-1.887406	0.0858	LNAGR	0.720074	0.084032	8.569003	0.0000
LNAGR	0.319473	0.424259	0.753013	0.4673	LNGDPC	0.338342	0.075334	4.491224	0.0006
LNGDPC	1.022397	0.198068	5.161859	0.0003	C	16.69534	1.749685	9.541911	0.0000
C	29.00327	11.17725	2.594849	0.0249					
Model 3: Dependent Variable: LNFS					**Model 4: Dependent Variable: LNGDPC**				
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**	**Variable**	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.**
No long-run equation – test bounds confirm no long-run relationship equation; we estimate just a short-run equation.					LNRF	0.672812	0.345697	1.946245	0.0651
					LNFS	0.030238	0.192366	0.157191	0.8766
					POP	2.895093	0.461497	6.273272	0.0000
					LNAGR	-0.678583	0.302010	-2.246887	0.0355
					C	-27.48108	3.816221	-7.201123	0.0000

Source: the authors.

Diagnostic Tests

Tables 8 and 9 in the appendix describe diagnostic tests for our ARDL models. These tables display the number of tests without problems related to autocorrelation, heteroskedasticity, and normality (figure 6). Notably, all probabilities exceeding 5% indicate that there are no problems in our models.

Also, the number of recursive residual cumulative (CUSUM) and square cumulative of the residual recursive (CUSUMSQ) tests show the absence of misspecification evidence and expected instability (figure 7 in appendix).

VI. Discussions and policy implications

The analysis of results obtained from ARDL models provides a deeper understanding of the effects of climate change on food security and sustainable development in Saudi Arabia. Applying the bounds testing approach for cointegration confirmed the existence of long-term relationships between the studied variables, thus justifying the use of this econometric methodology.

The empirical results across the four models elucidate complex interdependencies between climate change, food security, and economic dynamics in Saudi Arabia. Statistically, the models demonstrate robust explanatory power, with adjusted R^2 values ranging from 0.464 (Model 3) to 0.806 (Model 1), indicating that the selected regressors explain 46.4–80.6% of variations independent variables.

The error correction terms (ECTs) reveal distinct adjustment dynamics: Model 1 (EFP) exhibits a rapid annual correction rate of 147% (ECT = -1.47, $p < 0.01$), Model 2 (RF) shows a 321% adjustment speed (ECT = -3.21, $p < 0.01$), and Model 4 (GDPC) reflects an 80% convergence rate (ECT = -0.80, $p < 0.01$). These results underscore the responsiveness of Saudi Arabia's ecological and economic systems to disequilibria. In contrast, Model 3

(FS) lacks cointegration (F-statistic = 2.01, below critical bounds), implying no stable long-term relationship for food security, likely due to exogenous factors such as global market fluctuations or policy shifts not captured in the model.

The first model, a crucial part of our research, delves into the impact of climatic and economic variables on the ecological footprint (LNEFP). The findings are significant, with variations in average annual rainfall (LNRF), food production (LNFS), agricultural value added (LNAGR), population (LNPOP), and GDP per capita (LNGDPC) explaining a substantial 91% of the variations in the ecological footprint. The obtained F-statistic of -1.4695 further underscores the importance of these variables, indicating a significant relationship at a 1% significance level.

An increase in rainfall (LNRF) has a significant positive effect on land's biological productivity (Li et al., 2015). At the same time, population growth (LNPOP) exerts negative pressure by increasing the consumption of natural resources and CO_2 emissions (Thi Mai et al., 2024). The Durbin-Watson statistic (2.4989) confirms the absence of autocorrelation issues. In the long run, the ecological footprint is negatively influenced by population growth and extreme precipitation, illustrating the impact of climate change on environmental sustainability and the renewability of natural resources (Pan et al., 2023).

In this Model, long-run elasticities highlight the environmental cost of economic growth, with GDPC exerting a significant positive impact (+1.02, $p < 0.01$), while population (POP: -2.06, $p < 0.10$) and rainfall (RF: -2.24, $p < 0.05$) mitigate ecological pressures, albeit indirectly. Short-run results reveal that lagged food security (LNFS) and GDPC reduce EFP (-0.80 and -1.12, respectively), suggesting immediate policy interventions in these sectors can effectively curb environmental degradation, offering a beacon of hope in the face of climate change.

The second model measures the effect of economic and agricultural variables on rainfall (LNRF). The results reveal an inverse relationship between food security (LNFS), population (LNPOP), agricultural value added (LNAGR), and GDP per capita (LNGDPC) with rainfall. The F-statistic of -6.181902 indicates a significant relationship at a 1% significance level, with a coefficient of determination ($R^2 = 89\%$), demonstrating that these variables largely explain the variability in precipitation.

The intensification of economic and agricultural activities leads to increased greenhouse gas emissions, disrupting rainfall patterns in Saudi Arabia. In the long run, agricultural value added and GDP per capita positively impact rainfall, underscoring the urgent need for more balanced economic dynamics that could favorably influence climatic conditions (Atchadé & Nougbodé, 2024).

The second Model (RF) identifies population growth (POP: -1.86, $p < 0.01$) and agricultural expansion (AGR: +0.72, $p < 0.01$) as key long-term drivers of rainfall variability, with short-term dynamics showing volatile interactions between population, agriculture, and GDPC (Bouteska et al., 2024).

The third model analyzes the impact of variables on food security (LNFS). The study finds that the ecological footprint (LNEFP) significantly negatively affects food security due to

land overexploitation and environmental pollution (Bala & Hossain, 2010). With an F-statistic of -3.995152 and an R^2 of 70%, the results indicate that increased CO_2 emissions and the deterioration of natural resources reduce the agricultural sector's ability to meet the growing food demands of the Saudi population (Mahmood et al., 2019).

The study also highlights that economic growth focused solely on GDP per capita (LNGDPC) does not necessarily improve food security, emphasizing the need to manage natural and agricultural resources effectively. Indeed, the short-term equation reveals that agricultural output (LNAGR: -1.65, $p < 0.01$) and GDPC (-0.30, $p < 0.05$) negatively influence food security, pointing to structural inefficiencies in translating economic gains into food accessibility (Satrovic et al., 2024).

The fourth model explores the influence of variables on GDP per capita (LNGDPC). The analysis shows that agricultural value added (LNAGR) positively contributes to economic growth, whereas the ecological footprint (LNEFP) and increased carbon emissions have a negative effect on GDP per capita (Raihan, 2023).

The F-statistic of -6.871949 and an R^2 of 80% indicate that these variables largely explain variations in GDP per capita. The overexploitation of natural resources and the adverse effects of climate change hinder long-term economic development. These findings highlight the importance of considering the interactions between climate, agriculture, and economic development to understand the country’s structural challenges better.

The model also underscores rainfall’s positive long-run elasticity (+0.67, $p < 0.10$), while agriculture (AGR: -0.68, $p < 0.05$) exhibits a paradoxical negative effect, signaling diminishing returns from resource-intensive farming. Short-run estimates further emphasize rainfall’s immediate economic benefits (+0.26, $p < 0.05$).

Policy Implications and Recommendations:

The analysis of results highlights several challenges and opportunities related to the interactions between climate, agriculture, and the Saudi economy. Sustainable resource management must be a priority, particularly by strengthening sustainable agricultural practices, optimizing water use, and reducing the ecological footprint (LNEFP). Improving agricultural infrastructure, supporting research on resilient crops, and promoting agroecology are essential measures to ensure sustainable food production. Additionally, transitioning to renewable energy sources and adopting clean technologies must be accelerated to limit greenhouse gas emissions and mitigate the effects of climate change (Kabeyi & Olanrewaju, 2022).

Food security (LNFS) should be strengthened by reducing import dependence and diversifying agricultural production sources (Sukanya, 2024:pp 229–258). Modernizing storage and distribution infrastructure, as well as improving access to financing for farmers, will help enhance the sector’s resilience to climate shocks (Юзефович et al., 2024:pp 224-232.). Developing public policies promoting responsible consumption and less resource-intensive food production is also crucial (Lorek & Spangenberg, 2014:pp 33–44). Climate change adaptation must be reinforced by improving climate monitoring systems, investing in resilient infrastructure, and implementing sustainable urbanization policies. Integrating

nature-based solutions, such as reforestation, water resource management, and ecosystem preservation, will help reduce the negative impacts of climate change on the Saudi economy and society (Olgun et al., 2024; Gebrael et al., 2024).

Adopting an integrated approach that links the Economy, agriculture, and the environnement is essential to ensuring sustainable development and enhancing resilience to climate challenges in Saudi Arabia (Alotaibi et al., 2024:pp 1-21 ;Al-Khateeb et al., 2021:pp1-19 ;Rahman et al., 2022:pp1-19).

These findings necessitate a multi-pronged policy framework. First, the GDPC-EFP nexus in Model 1 calls for decoupling economic growth from environmental harm via green industrialization, renewable energy investments, and carbon pricing mechanisms. Second, Model 2's rainfall vulnerabilities demand integrated water management strategies, including aquifer protection, desalination innovation, and policies to curb urban sprawl's strain on water resources. Third, Model 3's instability in food security underscores the urgency of diversifying food imports, incentivizing vertical farming, and strengthening social safety nets to buffer against supply chain disruptions.

In general, the four short-term models confirm the negative impact of climate change on food security in Saudi Arabia and its ability to meet the food needs of both the current population and future generations. This is reflected in a significant gap in the Kingdom's ability to achieve self-sufficiency in resources. This gap reached approximately 0.7 gha, while the per capita demand for resources was 5.75 gha, resulting in a negative deficit of -5 gha.

Notes

(1) https://www.state.gov/reports/2024-investment-climate-statements/saudi-arabia/
(2) www.FoDaFo.org
(3) scholars, students, researchers, and collaborating organizations working together to advance the measurement of Ecological Footprint and Biocapacity and the application of these measures around the world, Toronto, Cañada. https://footprint.info.yorku.ca/
(4) https://www.footprintnetwork.org/our-work/ecological-footprint/
(5) https://www.footprintnetwork.org/our-work/ecological-footprint/
(6) https://www.footprintnetwork.org/resources/glossary/
(7) https://www.footprintnetwork.org/2022/07/13/food-security-in-a-world-of-overshoot/

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Appendix

Table 8. *Breusch-Godfrey LM test for autocorrelation*

Lags(p)	F	df	Prob > F	Decision
Model 1				
1	1.463880	1,12	0.2541	No serial correlation
2	0.702876	2,11	0.5204	
Model 2				
1	3.671147	1,12	0.0795	No serial correlation
2	0.702876	2,11	0.0776	
Model 3				
2	1.266028	2,18	0.3059	No serial correlation
Model 4				
2	0.650354	2,19	0.5331	No serial correlation

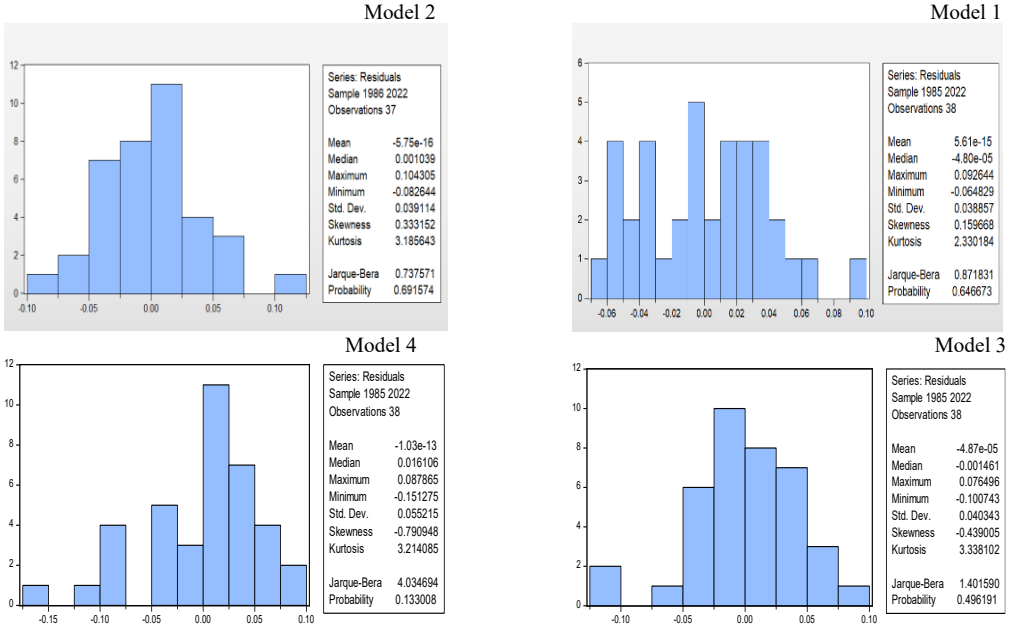
Source: the authors.

Table 9. *White test for heteroscedasticity*

Lags(p)	Value	df	Prob	Decision
Model 1				
F-statistic	1.902112	26,11	0.1319	No heteroscedasticity
Obs*R-squared	31.08576	26	0.2251	
Scaled explained SS	1.732452	26	1.0000	
Model 2				
F-statistic	0.700704	23,13	0.7794	No heteroscedasticity
Obs*R-squared	20.47998	23	0.6128	
Scaled explained SS	2.762880	23	1.0000	
Model 3				
F-statistic	1.434057	18,19	0.2212	No heteroscedasticity
Obs*R-squared	21.88861	18	0.2370	
Scaled explained SS	7.094846	18	0.9893	
Model 4				
F-statistic	1.092957	16,21	0.4174	No heteroscedasticity
Obs*R-squared	17.26590	16	0.3686	
Scaled explained SS	5.837474	16	0.9898	

Source: the authors.

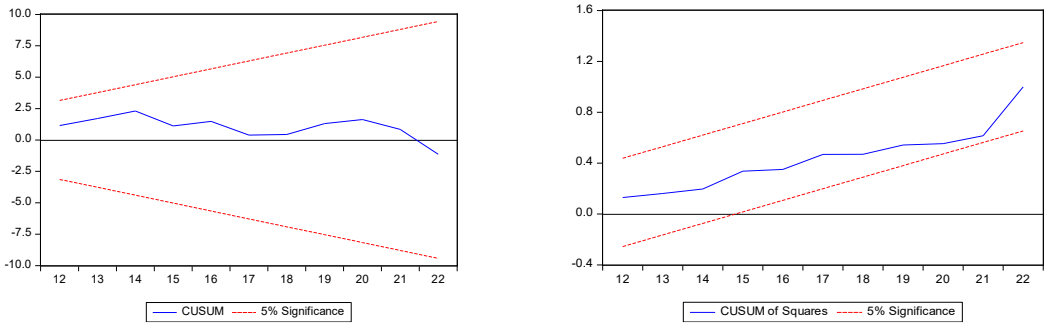
Figure 6. *Skewness/Kurtosis and Jarque-Berra tests for normality*



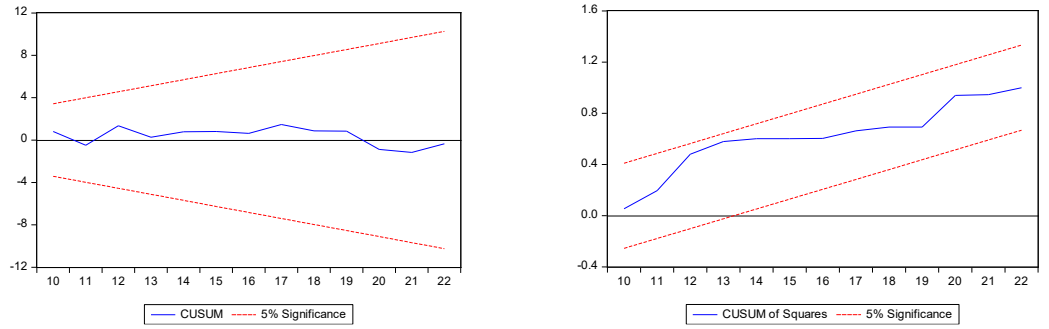
Source: the authors.

Figure 7. *CUSUM CUSUMQ test stability*

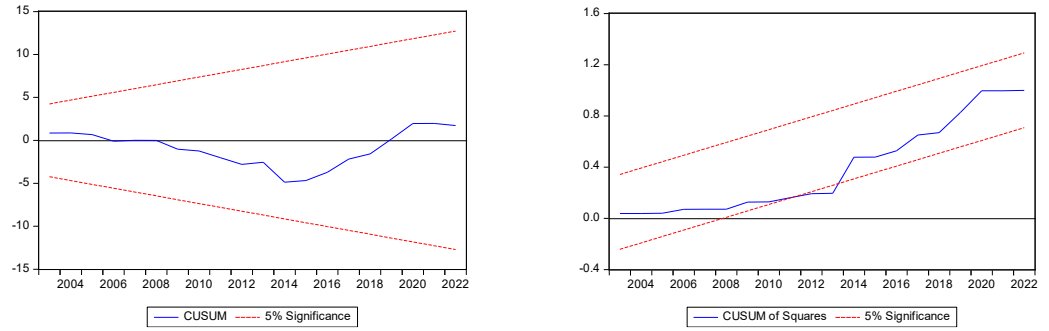
Model 1



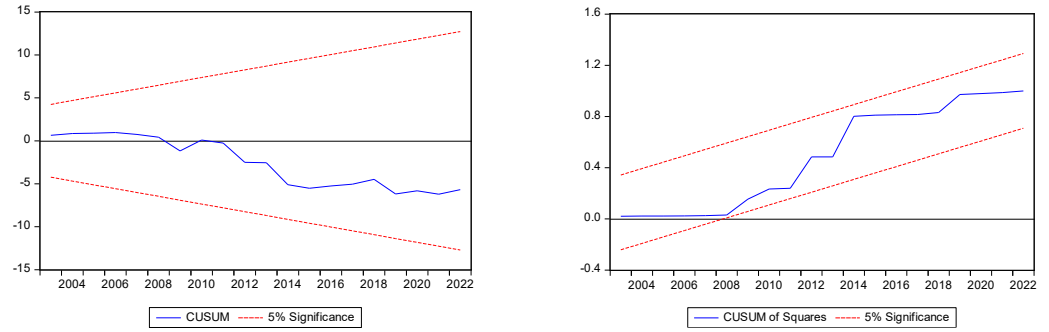
Model 2



Model 3



Model 4



Source: the authors.