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Research article

An analysis of climate impacts on agriculture production: Evidence from Türkiye by BMA and A-ARDL approaches

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ABSTRACT

This study investigates the impact of climatic factors on agricultural output between 1970 and 2022 in Türkiye. The Bayesian Model Averaging (BMA) method was utilized to select the independent variables for the model. The augmented ARDL (A-ARDL) approach was employed to analyze the cointegration relationship between the variables. Then, the CCR, DOLS, and FMOLS techniques were applied to assess the long-term dynamics. The key findings of the study are as follows: (i) The BMA analysis identified the carbon dioxide emissions, cultivated agricultural area, minimum average temperature, and 10 cm ground temperature as the significant independent variables. (ii) The A-ARDL results indicate a long-term association between the selected variables. (iii) The minimum average temperature is positively associated with the agricultural sector's share in GDP. (iv) Increases in carbon dioxide emissions, 10 cm ground temperature, and cultivated agricultural area were found to decrease the agricultural sector's share in GDP. In summary, the findings of study confirms the multi-dimensioned and non-linear character of climate-agriculture relations, challenging overly simplistic interpretations. From a policy perspective, the evidence puts emphasis on the need for climat-smart agricultural policies that bind together temperature regulation, emissions reduction, and efficient land use. Such insights are particularly significant for nations such as Türkiye that experience both extreme climatic volatility as well as structural challenges within their agricultural systems.

1. Introduction

From the Industrial Revolution to the present, 2023 has been recorded as the hottest year in terms of instrumental global surface temperature measurement (Copernicus Climate Change Service - CCCS, 2024). Advanced climate models predict that average temperatures will rise by 1.4–5.8 Celsius by the end of the century. (Intergovernmental Panel on Climate Change – IPCC and Masson – Delmotte, 2021). All these increases show that uncontrolled anthropogenic greenhouse gas emissions are causing global climate change. Long-term global climate change includes regional temperature increases and changes in meteorological factors like precipitation patterns, pressure systems, and humidity (Karl and Trenberth, 2003). The distribution of climatic condition deviations is said to be heterogeneous across nations. (IPCC, 2014). The frequency and severity of extreme weather events are predicted to rise in the upcoming years if nothing is done. Therefore, it is crucial to look at how the negative externality driven by climate change affects economic processes.

The agricultural sector is one of the most impacted by climate change when it comes to economic activities (Rosenzweig and Parry, 1994; Randhir and Hertel, 2000; Deschenes and Greenstone, 2007). Technological advancements in agriculture have an impact on productivity, but they are strongly correlated with climate and agricultural subsectors. Climate-related anomalies are known to reduce agricultural production and cultivable land (Aggarwal et al., 2010; Karahasan and Pınar, 2023), reduce farmer incomes (Mishra and Sahu, 2014), shift agricultural employment (Kjellstrom et al., 2009), raise adaptation costs (International Food Policy Research Institute – IFPRI, 2009), and cause

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issues with the food supply (FAO, 2009). Among these issues, the effects of climate change on agricultural production are of great importance for economies with a high reliance on agriculture-based industries, intensive agricultural employment, and low adaptation skills.

Due to its geographic location, the significance of the agricultural industry, and the effects of climate change, Türkiye is at the center of this discussion. It is stated that deviations in climatic factors due to global climate change are more intense at the 40–70° north parallels (Türkeş, 2007). Being partially between these parallels, Türkiye is vulnerable to global climate change. In different regions of Türkiye, the rise in greenhouse gas emissions, temperature increases, changes in soil surface temperature, and the use of agricultural land significantly affect the quality and quantity of agricultural production (Kurukulasuriya and Mendelsohn, 2008). Although the agricultural sector has a decreasing share in the Turkish economy, it maintains its strategic importance in terms of employment, food security, and rural development. In addition, the share of the agricultural sector, along with its sub-sectors, in GDP has been decreasing over time and currently stands at around 5–6 % (World Bank, 2024a). Agriculture's economic share has declined over time, but in 2022 it accounted for roughly 16 % of the total employment (Turkish Statistical Institute, 2024aa). With its semi-arid climate and Mediterranean basin location, Türkiye is one of the nations most vulnerable to the possible consequences of climate change (IPCC, 2007). In addition to climatic hazards on agricultural production, the Turkish agricultural sector also has structural problems. The agricultural sector is more vulnerable to climate change because of the traditional structure of agriculture, the dispersed and fragmented structure of agricultural lands, the cost increases caused by economic instability, and the reform laws put in place following the crisis (Arı, 2006; Pamuk, 2009; Eştürk and Ören, 2014). These vulnerabilities make it difficult to investigate the impacts of climate change on the agricultural sector. Again, it is observed that the indicators related to climate change are numerous and not standardized. Each climatic factor may have a different effect on the various sub-sectors that make up the agricultural sector, such as crop production, livestock, and aquaculture. Therefore, the effects of climate change on agriculture appear as a complex equation with many unknowns. The primary motivations for this study stem from the pressing need to improve comprehension of the specific effects of factors on agricultural output, particularly in the context of Türkiye, given its unique geographic and economic characteristics. In this regard, this article is designed to investigate a number of critical research questions: (i) Which climate variables influence Türkiye's agricultural production share of GDP?; (ii) Which climatic factor has a greater impact on the share of agricultural production?; (iii) Which strategies can be implemented to prevent the decline in the share of agricultural production?

In addition, previous studies have largely looked at either the overall relationship between climate and agriculture or individual climatic variables separately and thus provided partial and disconnected insights on the general climate-agriculture relationship. There is consequently a considerable knowledge gap with regard to fully determining and quantifying the effects of different climatic factors on agricultural output in the case of Türkiye. This research is aimed at precisely filling this research gap by synthesizing several climatic variables analytically within a unified research framework, facilitating comprehensive and policy-relevant insights.

Considering above-mentioed facts, the understanding the long-term effects of climate factors on the Turkish agricultural sector and evaluating these effects in economic terms plays a critical role in directing the policies to be implemented. In this context, the primary goal of this study is to investigate the impact of climatic factors on Türkiye's agricultural output using data from the period from 1970 to 2022. This research makes original contributions to current literature by overcoming previous constraints in three ways. First, it fully considers several climatic variables simultaneously, which makes the explanatory power and relevance of the findings. Second, the research applies Bayesian Model Averaging (BMA) to tightly find statistically important variables, thus eliminating model specification errors and improving the stability of forecasts. Third, it applies the A-ARDL technique introduced by Sam et al. (2019) to effectively estimate long-term associations as well as structural breaks, especially applicable for analyzing small-sized datasets. The resulting results deliver accurate, evidence-based policy recommendations specific to the climate-related issues confronting Türkiye's agricultural industry.

The study consists of six sections, and following the introduction, the development of Türkiye's agricultural sector and policy frameworks are given in section 2. section 3 presents the summary of empirical studies and backgrounds. In the fourth section, detailed information will be provided about the variables analyzed and the econometric methodology. The empirical results and discussions are given in the fifth section. section 6 focuses on the conclusion and policy insights.

2. Development of Türkiye's agricultural sector and policy frameworks

The Turkish economy ranks among the world's top 20 economies in terms of gross domestic product (GDP) size (Ozcan et al., 2025). In 2023, the total GDP amounted to approximately $1.1 trillion, with the agricultural sector accounting for around 6.15 % of this figure (World Bank, 2025). Although the share of total agricultural output in GDP has steadily declined since 1980, the agricultural sector still retains its significance for the Turkish economy.

Fig. 1 presents data on the value added by agriculture, forestry, and fishing as a percentage of GDP for the period 1980–2023. In 1980, the share of agricultural output in total GDP was 26.14 %, but it steadily declined until 1992, falling below 15 %. Despite a short-term increase observed up to 1996, the share of agricultural output in GDP dropped below 10 % for the first time in 2001. This decline coincided with the effects of the economic crisis experienced in 2001. A similar downward trend continued in the following years. According to 2023 data, the share of agricultural output in GDP stands at 6.15 %.

Although a decline in the share of agricultural output within GDP was observed during the 1980–2023 period, there was a significant increase in the absolute value of agricultural value added over the same timeframe. While the agricultural value added was $17.9 billion at the beginning of 1980 and decreased until 1984, it showed a rapid increase between 1985 and 1998—aside from a few exceptional years—reaching $33.4 billion. Following this period, a decline was observed in agricultural value added until the 2001 economic crisis. Starting from 2002, the value began to rise again, reaching its highest level in Türkiye at $69.6 billion in 2010. After this peak, there was a substantial decrease in agricultural value added. By 2021, it had steadily declined to $45.3 billion, but in 2023, it made a strong recovery, rising sharply to $68.8 billion.

Fig. 3 presents data on employment in the agricultural sector. At the beginning of the 1990s, nearly half of Türkiye's total labor force was employed in agriculture. This share remained above 20 % until 2016. Except for some exceptional years in the mid-2000s, the share of

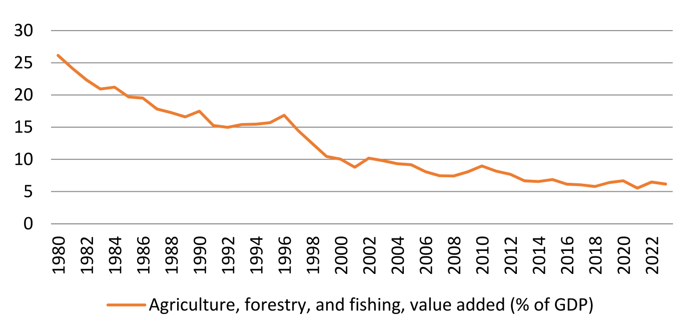

Fig. 1. Agriculture, forestry, and fishing, value added (% of GDP)
Source: World Bank (2025).

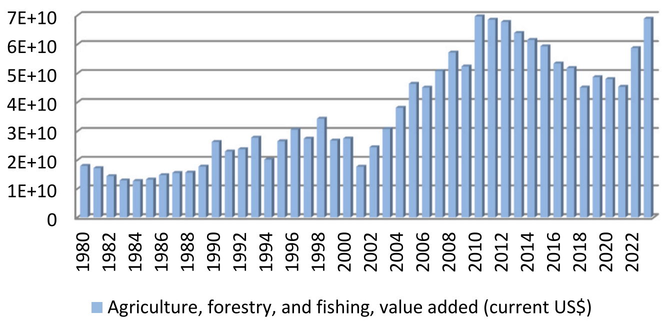

Fig. 2. Agriculture, forestry, and fishing, value added (current US$)
Source: World Bank (2025).

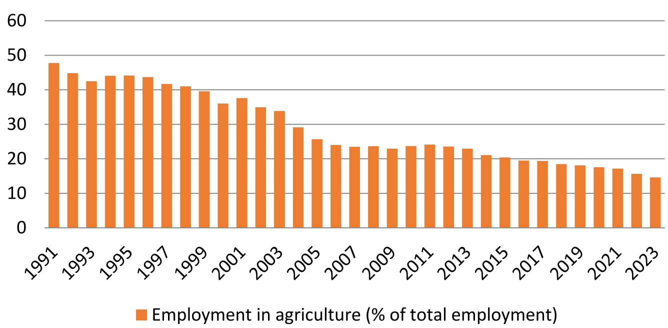

Fig. 3. Employment in agriculture (% of total employment)
Source: World Bank (2025).

agricultural employment in total employment has shown a continuous decline. However, the relative share of agriculture in total employment still remains high. As of 2023, 14.64 % of total employment in Türkiye is still in the agricultural sector. Globally, this rate is about 26 %, while it stands at 29 % in middle-income countries, 4.45 % in OECD countries, 3.79 % in the European Union, and 3.15 % in developed countries (World Bank, 2025).

Although Türkiye has significant potential in the agricultural sector, actual production levels remain quite low, as seen in the figures above. The fact that agricultural imports have recently become a major expenditure item is clear evidence of this situation (Sertoğlu and Doğan, 2016). While the production gap in agriculture is one of the causes of economic losses, it is essential to implement effective policies for the sector. At this point, the main goals of Turkish agricultural policies can be listed as ensuring food supply security, increasing agricultural productivity, developing crop patterns, promoting the use of innovative technologies in agriculture, supporting rural development, and ensuring continuity in agricultural income (Akder, 2007). Although these policy objectives are realistic, the constraints of globalization, economic transformations, macroeconomic instability, privatizations, and seasonal fluctuations place a burden on the agricultural sector. In terms of solving these issues, the policies implemented appear to lack structural reform specific to agriculture. For example, addressing the production deficit through imports endangers food supply security and complicates the management of foreign exchange reserves. Additionally, agricultural production being vulnerable to seasonal effects—largely due to climate change-induced anomalies—disrupts the supply-demand balance and leads to increases in the prices of basic food items (Dudu and Çakmak, 2017). However, these price hikes are often addressed through regulated sales that do not align with free market mechanisms.

Agricultural policies in Türkiye aim to support both consumers and producers. Although input subsidies and selective credit policies benefit the sector, the limited scope of these practices, bureaucratic obstacles, and mismanagement prevent the expected outcomes from being realized (Yılmaz, 2006). For instance, the restriction of input subsidies solely to fertilizer use reflects the narrow scope of these policies. The challenges in designing agricultural policies are not only domestic but also stem from restrictions imposed by international organizations. Credit agreements signed with institutions such as the IMF, World Bank, and World Trade Organization negatively influence the design of Türkiye's agricultural policies (Aydın, 2010). The economic reforms initiated with the January 24, 1980 decisions marked a significant transformation for Türkiye, but also reduced the number of agricultural products eligible for price support. Furthermore, as part of agreements signed with the IMF and World Bank in 1999, the government ceased purchasing agricultural products, initiating a period of increased external dependency in agriculture. Additionally, economic instability has led to rising costs for key agricultural inputs such as fertilizer, fuel, electricity, and water, significantly impacting farmers' incomes. As a result, arable lands are left unused, inheritance practices reduce farm sizes, and limited access to technology has become a chronic problem in Turkish agriculture (Dudu et al., 2015). Particularly due to fragmented land ownership, farming has become a family-based subsistence activity, and agricultural production continues largely at subsistence levels. Privatization efforts have made it increasingly difficult for small-scale subsistence farmers to compete with large agribusinesses, making them vulnerable to market conditions (Aydın, 2010).

Agricultural policies should be designed in a way that allows producers to earn fair compensation for their labor, while ensuring consumers have access to affordable and sufficient food supplies. In this context, the introduction of direct income support in 2000 marked a significant shift in agricultural policy in Türkiye (Demirdöğen et al., 2016). Direct income support refers to payments made directly to agricultural producers to increase their income. This support includes payments related to natural disasters, losses, per animal or per hectare subsidies, and storage assistance. Although direct income support provides short-term benefits, addressing long-term structural issues also requires the integration of subsidies, preferential loans, and insurance schemes (Koç et al., 2019). Furthermore, the government must play a leading role in promoting the use of modern agricultural techniques, particularly in sector-specific applications. Agricultural production that utilizes technological innovations will increase productivity, ensure food supply security, and enhance the country's export potential.

Finally, a landmark decision was made on April 25, 2006, in Türkiye regarding agricultural subsidies. It was decided that the total amount allocated to agricultural support from the national budget could not be less than 1 % of the gross national product. However, the actual impact of this decision on agricultural production depends on how the funds are used and what they cover. Among the chronic problems of the agricultural sector, the effectiveness of these allocated funds remains a critical topic of debate (Burrell and Kurzweil, 2007). Therefore, when designing agricultural policies, Türkiye must first take into account the structural and functional problems unique to its agricultural sector.

3. The linkages of climate change and agricultural production: backgrounds and literature surveys

The agricultural industry relies heavily on environmental and climatic factors as inputs (Rosenzweig and Parry, 1994; Reilly, 1995). Given its significance, agricultural production as a whole as well as its subsectors may be impacted by global climate change and the variables that contribute to it (Adams et al., 1990; Parry, 1992). Thus, the first thing that has to be addressed is the fact that climate change and the agriculture industry are mutually interacting. Energy consumption rises as a result of agricultural production activities (such as tillage, fertilizer, and spraying) (Bayraç and Doğan, 2016). Using non-renewable energy sources that are more affordable and easily accessible to meet the aforementioned activities results in a rise in atmospheric carbon dioxide emissions (IPCC, 2007). Calculations indicate that the agricultural sector is responsible for around 20 % of the rise in greenhouse gasses, which are the primary driver of climate change (Pathak and Wassmann, 2007). Currently, the climate crisis has a detrimental impact on the agricultural sector, even while agricultural operations enhance climate change and increase anthropogenic greenhouse gas emissions. Due to this reciprocal relationship, the agricultural industry is vulnerable to the effects of climate change (Deressa et al., 2005; Howden et al., 2007). The agricultural sector, on the other hand, is strategically significant in terms of creating jobs, generating basic livelihoods, producing resources for foreign exchange, and supplying industrial sector inputs (Amponsah et al., 2015). However, climate change-related variations in agricultural productivity and quality lead to adjustments in economic balances. It is challenging to manage food inflation since declining agricultural yields raise the costs of agricultural items (IPCC, 2013; Stevanovic et al., 2016). A rise in agricultural reliance and the current account deficit are the results of poor agricultural production and the current demand being satisfied by imports (Randhir and Hertel, 2000). The inability to adopt climate-compatible farming methods leads to a decrease in the farmed land area, which raises agricultural unemployment (Kjellstrom et al., 2009). This circumstance is one of the causes of regional migration in countries with a predominately agricultural economy. Maintaining budget discipline will be challenging due to the rise in state subsidies provided to farmers in an effort to lessen the adverse impacts of climate change on the agricultural industry (Kurukulasuriya and Rosenthal, 2003).

Agricultural productivity is affected differently by global climate change based on the variety and intensity of weather-related variations as well as response abilities (Antle, 1995; Dellal and McCarl, 2010). Producing plants (annual and perennial agricultural goods), livestock, and aquaculture (fresh and saltwater fishing) are all considered to be part of the agricultural industry in a broad sense. Currently, the relationship between precipitation and average temperature on plant output is crucial (Dellal and Butt, 2005; Deschenes and Greenstone, 2007; Jönsson, 2011). Global warming-induced temperature increases result in changes to the soil's organic structure and a drop in humidity. Farmers' focus on irrigation techniques to ensure sustainable output raises soil salt levels and production costs (Aydınalp and Cresser, 2008). Furthermore, the productive portion of the soil is lost as a result of excessive rainfall brought on by shifts in precipitation regimes (Rosenzweig et al., 2002). Therefore, hydrological droughts and excessive rainfalls occurring more frequently and intensely with climate change lead to soil erosion. In addition to all of these, agricultural production and product quality are adversely impacted by the growing range of illnesses and pests found in agricultural goods (FAO, 2009; Chandio et al., 2020).

Activities related to livestock and fisheries production, which are subsectors of agriculture, are indirectly impacted by climate change (Bosello and Zhang, 2005). Particularly, irregularities in rainfall patterns alter the circumstances under which natural grasses thrive in pastures, necessitating the supply of feed (Hertel, 2018). Feed consumption, milk production, and animal death or birth rates are all negatively impacted by the susceptibility of commercially important animals to increases in average temperature (Barua and Valenzuela, 2018). There are also impacts on the fishing industry from sea surface warming (Perry et al., 2005) and acidification (Orr et al., 2005). The term "global warming" refers to the widespread warming of both land and ocean surfaces. Commercially significant fish species migrate to more physiologically favorable water habitats as a result of sea surface warming (Tayyar, 2022). Furthermore, when sea temperature increases, economically valuable species are replaced by invasive species with no commercial value, which hurts the fishing sector, which supplies inexpensive protein. Another reason that negatively affects the fishing industry is the problem of acidification (the other carbon dioxide problem or the evil twin of global warming) (Tayyar, 2023). The process by which carbon dioxide gas in the atmosphere interacts with the sea to raise the acidity of saltwater is known as acidification (Caldeira and Wickett, 2003). The growth, reproduction, behavior, energy usage, and immunity of marine species are all adversely impacted by the waters' growing acidity (Kroeker et al., 2013). Acidification's detrimental effects lead to a decline in the productivity and variety of marine organisms that are commercially valuable yet susceptible to change (Royal Society, 2005). It is obvious that uncontrolled carbon dioxide emissions will increase global warming and acidification, which will lower fishing industry earnings while ensuring the security of the food supply and cost-effective protein.

Although they are rare, climate change does have some beneficial consequences on the agriculture industry. These benefits include the fertilizing action of carbon dioxide, a rise in crop yields, modifications to crop patterns, and the growth of agricultural cultivated areas (Bosello and Zhang, 2005; Mendelsohn, 2009; Olesen et al., 2011). The rate of carbon dioxide has a direct correlation with photosynthesis, which plays a significant role in plant development. In this way, photosynthesis is strengthened and plant growth and output are accelerated by the rise in carbon dioxide that results from climate change (Özdoğan, 2011; Hertel and Lobell, 2014). Furthermore, it is suggested that in the middle and northern latitudes, temperature increases of 1–3° due to climate change will result in an increase in the usage of agricultural land (Zabel et al., 2014). The distributional impacts of climate change on the agricultural output of countries in the northern and southern latitudes are currently evident. According to studies, the agricultural sector's gains and losses are altered by climate change, which affects a countries' competitive advantages (Julia and Duchin, 2007; Iglesias et al., 2011; Barua and Valenzuela, 2018). Once more, climate change has made it possible for goods to be planted earlier and harvested later, resulting in high-value economic patterns (Çakmak and Gökalp, 2011; Deniz and Hiç, 2022). Climate change thus raises the proportion of agricultural production in GDP because of the rise in production levels.

Climate-compatible agriculture is necessary due to both the positive and negative consequences of climate change on the agricultural sector. Adaptation costs rise when climate change is fought or used to one's benefit (Wall and Smit, 2005; FAO, 2010). Due to this circumstance, the agriculture industry is at danger and susceptible to climate change, particularly in low-income nations (Carleton and Hsiang, 2016). Because of its significance, a lot of research has been done on the relationships between climatic factors and agricultural output. The effects of climatic factors on agricultural production using various econometric methods for countries and country groups are given in Table 1.

The impact of climatic conditions on agricultural output has been studied using mostly time series and panel data techniques for country or country groups, according to the reviewed research. Most evaluations show that while there is a positive relationships between rising precipitation and agricultural productivity, there is a negative relationships between rising average temperature and agricultural production. However, existing studies do not appear to examine all climatic factors that have potential effects on agricultural production.

As can be seen Table 1, this research is different from previous studies due to a more holistic and integrative perspective on the analysis of climatic variables. However, most studies examine individual climate variables separately or utilize limited analytical frameworks in the case of Türkiye, whereas our research synthesizes several climatic variables determined through stringent Bayesian Model Averaging. In adition, our research utilizes the A-ARDL method, which adds strength against possible structural breakpoints and provides accurate long-term predictions. Through holistically integrating several of the identified climatic variables, our research not only provides methodologically sound findings but also is practically useable for policy formulation and implementation.

4. Data set and econometric methodology

4.1. Data set

In this section, for the purpose of this study, related information on climatic variables that are considered to be effective on agricultural

Table 1
Summary of empirical studies on climate change and agricultural production.

Study and Year	Period	Country (ies)	Methodology	Agricultural Production Interaction
Deressa et al. (2005)	1977–1998	South Africa 11 Countries	Ricardian Analysis	Winter Temperatures (−) Summer Temperatures (+)
Molua and Lambi (2006)	2002–2003	Cameroon	Ricardian Cross-Sectional Analysis	Precipitation (+) Temperature (−)
Brown et al. (2010)	1961–2003	133 Countries	Fixed Effects	Precipitation (+) Temperature (−)
Jönsson (2011)	1984–2009	Mauritius	Ricardian Cross-Sectional Analysis	Temperature (−) Precipitation (+)
Akram (2012)	1972–2009	8 Asian Countries	Fixed Effects and SUR	Precipitation (+) Temperature (−)
Lee et al. (2012)	1998–2007	13 Asian Countries	Fixed Effects	Precipitation in Summer (+) Temperature in Summer (+)
Başoğlu and Telatar (2013)	1973–2011	Türkiye	Regression Analysis	Precipitation (+) Temperature (−)
Belloumi (2014)	1961–2011	11 African Countries	Two-ways Fixed Effects	Precipitation (+) Temperature (−)
Amponsah et al. (2015)	1961–2010	Ghana	ARDL	CO2 Emission (−)
Loum and Fogarassy (2015)	1960–2013	Gambia	Regression Analysis	Marginal Precipitation (−) Marjinal Temperature (−) CO2 Emission (+)
Bayraç and Doğan (2016)	1980–2016	Türkiye	ARDL	Precipitation and CO2 Emission (+) Temperature (−)
Kumar et al. (2016)	1980–2009	India	State-wise Panel Analysis	Temperature (−)
Ali et al. (2017)	1989–2015	Pakistan	GLS	Minimum Temperature (+) Maximum Temperature (−)
Dumrul and Kılıçarslan (2017)	1961–2013	Türkiye	ARDL	Temperature (−) Precipitation (+)
Hayaloğlu (2018)	1990–2016	10 Countries	Fixed and Random Effects	Climate Change (−)
Chandio et al. (2020)	1968–2014	Türkiye	ARDL	Short and Long Term Precipitation (+) Temperature (−)
Ketema and Negesso (2020)	1980–2016	Ethiopia	ARDL	Temperature (−) Precipitation (+)
Akcan et al. (2022)	1985–2018	Türkiye	ARDL	Precipitation and Humidity (+) Temperature and Snow Covered Day (−)
El-Khalifa et al. (2022)	1990–2020	Egypt	ARDL	Temperature (−)
Mammo (2022)	1992–2017	Ethiopia	ARDL	Temperature (−) Yağış (−)

Source: The table was created by the authors of the study. The (+) sign in the table indicates that the relevant factor has a positive effect on the agricultural sector, while the (−) sign indicates a negative effect.

production is provided. We analyzed an annual time series from 1992 to 2021, dictated by the data availability for Türkiye. The variables used in our analysis are documented in Table 2.

Based on Table 2, AGDP is the dependent variable and all the remaining variables represent the independent variable group. AH, CO2, FCMGT, MAXT, MINT, NDWSC, PREC, TCMGT and TEMP variables show climate-related independent variables that may have an impact on agricultural production. Examining the studies conducted on the subject, expectations can be formed regarding the variables. Considering the results of previous analyses for Türkiye, it is expected that AH, CO2 and PREC had a positive effect on AGDP, while NDWSC and TEMP had a negative effect on AGDP. In the studies conducted for Türkiye, the effect of MAXT, MINT, FCMGT, TCMGT variables on AGDP was not analyzed. However, in parallel with the results of the studies conducted for other countries, it can be estimated that MAXT, FCMGT, TCMGT variables may affect the AGDP variable negatively and MINT variable positively. It is expected that an increase in AGAR, which is used in the study and has no relationship with climate, will increase agricultural production in GDP and accordingly increase AGDP. To address potential heteroskedasticity and interpret the coefficients as elasticities, all variables used in the analysis are transformed into their natural logarithmic form, except for dummy variables. This transformation helps to stabilize the variance and improve the interpretability of the model.

4.2. Econometric methodology

The estimation strategy adopted in this study is structured in multiple stages to ensure both model robustness and statistical validity. The steps are outlined below:

We computed partial and semi-partial correlation coefficients to assess the individual and unique contributions of each independent variable to the dependent variable (AGDP). This initial screening helps to detect spurious correlations and rank variables by influence. Next, we applied Bayesian Model Averaging (BMA) to address model uncertainty and identify the most statistically relevant explanatory variables. BMA evaluates all possible variable combinations (2ˆk models for k

Table 2
Data definition.

Symbols	Description	Unit	Source
AGAR	Agricultural cultivated area	Thousand Hectare	Turkish Statistical Institute (2024b)
AGDP	Share of agricultural production in GDP	%	World Bank (2024b)
AH	Average humidity	%	Turkish State meteorological Service (2024)
CO2	Carbon dioxide emissions	Million Tones	Global Carbon Atlas (2024)
FCMGT	5 cm ground surface temperature	Celsius	Turkish State meteorological Service (2024)
MAXT	Maximum temperature	Celsius	Turkish State meteorological Service (2024)
MINT	Minimum temperature	Celsius	Turkish State meteorological Service (2024)
NDWSC	Number of days with Snow Cover	Day	Turkish State meteorological Service (2024)
PREC	Precipitation	Millimeter	Turkish State meteorological Service (2024)
TCMGT	10 cm ground surface temperature	Celsius	Turkish State meteorological Service (2024)
TEMP	Average temperature	Celsius	Turkish State meteorological Service (2024)

predictors) and assigns posterior probabilities to each model based on fit, thereby minimizing omitted-variable bias. After selecting key variables using BMA, we tested for stationarity using the Fourier ADF-SB unit root test, which accounts for both structural breaks and nonlinearity in the series. Given that the variables are a mix of I(0) and I(1), we employed the Augmented ARDL (A-ARDL) bounds testing approach to examine long-run cointegration among the selected variables. The approach eliminates the degenerate cases often seen in traditional ARDL models and addresses endogeneity issues.After confirming the presence of long-run cointegration between varibales, we estimated the long-run effects of the explanatory variables on the dependent variable using the Canonical Cointegration Regression (CCR; Park, 1992), Dynamic Ordinary Least Squares (DOLS; Saikkonen, 1992; Stock and Watson, 1993), Fully Modified Ordinary Squares (FMOLS; Hansen, 1992a; Hansen, 1992b; Phillips and Hansen, 1990) estimators. Finally, diagnostic checks are performed (normality, autocorrelation, heteroskedasticity, stability, multicollinearity) to validate model specification and ensure the reliability of inference.

4.2.1. Partial and semi-partial correlation

Assume that the determinants of y are $x_1, x_2, \ldots, x_k$. Partial correlation between y and x_1 represents the correlation between y and x_1 under the assumption that all other $x's$ remain constant(Kim, 2015). A semi-partial correlation, also known as a parttial correlation, is a way to estimate the correlation that would exist between y and x_1 once all other x's effects are eliminated from x_1 but not from y. Both squared correlations calculate the percentage of 's variance that each predictor accounts for. The amount of the variance in y can be explained by x_1 only is indicated by the squared semipartial correlation between y and x_1. Another way to think of this squared correlation is as the drop in the model's R^2 value that happens when x_1 is taken out of the complete model. So, the squared semipartial correlations could be used as model selection criteria. The squared partial correlation between x_1 and y is the percentage of 's variance that can be accounted for by x_1 and not by any other x's. An estimate of the proportion of y's variance that cannot be explained by the other x's is thus provided by the squared partial correlation. x_i and x_j have the following partial correlation given x_k (Guliyev, 2024): The semi-partial correlation between x_i and x_j given xk is as follows, where r is the correlation coefficient:

Partial correlation between x_i and x_j given x_k

$$r_{ij|k} = \frac{r_{ij} - r_{ik}r_{jk}}{\sqrt{1-r_{ik}^2}\sqrt{1-r_{jk}^2}} \tag{1}$$

Semi-partial corelation between x_i and x_j given x_k is

$$r_{i(j|k)} = \frac{r_{ij} - r_{ik}r_{jk}}{\sqrt{1-r_{jk}^2}} \tag{2}$$

4.2.2. Bayesian Model Averaging

Bayesian Model Averaging (BMA) is a statistical approach that addresses model uncertainty by considering multiple models rather than relying to a unique model proposed by the researcher or found in the literature. Model uncertainty is an important issue, especially when working with a large number of independent variables, and incorrect variable selection can negatively affect the accuracy of estimation. BMA is designed to make the best predictions among different model variations and helps to avoid overfitting and the inclusion of unimportant variables in the model. In BMA, the analysis process considers all possible models and calculates the posterior probability of each model. Models that are less supported by the data receive a lower weight in the averaging process. Thus, the final estimation is based on a weighted average of all models. This approach ensures precision in the selection of relevant variables and avoids parameter overuse, producing more robust models.

BMA was developed by Leamer and Leamer (1978) by fitting model averaging to a Bayesian framework. This method provides a systematic approach to defining model weights as posterior model probabilities, and this framework provides a valid method for all data generation processes. BMA arises naturally by adapting a standard Bayesian estimation method to model averaging. Following the BMA approach, model M is treated as a random variable and its prior probability, P(M), is distributed over the model space. After observing the data, the likelihood, $P(D|M)$, which expresses the fit of the model with the data, is calculated. The posterior probability of the model is obtained using Bayes' Theorem:

$$P(M_j|D) = \frac{P(D|M_j)^* P(M_j)}{\sum_{k=1}^{M} P(D|M_k)^* P(M_k)} \tag{3}$$

Here, $P(D|M_j)$ is the marginal likelihood function of the j-th model and denotes the probability that the model produces data. The marginal likelihood for each model is obtained by integrating the parameters:

$$P(D|M_j) = \int P(D|\theta_j, M_j)^* P(\theta_j|M_j) d\theta_j \tag{4}$$

$P(\theta_j|M_j)$ refers to the a priori distribution of parameters. $d\theta_j$ is the integral variable of the parameters. $P(M_j)$ is the a priori probability of the j-th model, while $\sum_{k=1}^{M} P(D|M_k)^* P(M_k)$ is the sum of the marginal probabilities of all models. In the next step, the BMA estimator is estimated (Shao and Gift, 2014). For this, it uses the posterior estimates and posterior probabilities for each possible model. The BMA estimator for the parameter or variable of interest is defined by formula (3):

$$\hat{\theta}_{BMA} = \sum_{j=1}^{M} P(M_j|D)^* \hat{\theta}_j \tag{5}$$

Here, $\hat{\theta}_{BMA}$ is the BMA estimator, $P(M_j|D)$ is the posterior probability of the j-th model given data D, $\hat{\theta}_j$ is the estimator from the j-th model, and M is the number of all possible models.

4.2.3. Unit root test

Furuoka (2017) developed the Fourier ADF (FADF-SB) test In his study that allows for structural breaks in case the series are nonlinear and include structural breaks. Unlike the ADF-type ADF-SB test that takes into account structural breaks in the series, this test is a new unit root test that includes both structural breaks and nonlinearity of the series (Furuoka, 2017). The FADF-SB test is basically an extension of the ADF-SB test. These tests include time dummy variables to identify endogenous structural breaks, as in the Zivot and Andrews (1992) unit root test with structural breaks. The FADF-SB unit root test process can be based on the following equations.

$$\text{Model A}: \Delta y_t = \mu + \beta t + \rho y_{t-1} + \sum_{i=1}^{p} c_i \Delta y_{t-i} + \varepsilon_t \tag{6}$$

$$\text{Model B}: \Delta y_t = \mu + \beta t + \gamma_1 \sin\left(\frac{2\pi kt}{T}\right) + \gamma_2 \cos\left(\frac{2\pi kt}{T}\right) + \rho y_{t-1} + \sum_{i=1}^{p} c_i \Delta y_{t-i} + \varepsilon_t \tag{7}$$

$$\text{Model C}: \Delta y_t = \mu + \beta t + \delta DU_t + \theta D(T_B)_t + \rho y_{t-1} + \sum_{i=1}^{p} c_i \Delta y_{t-i} + \varepsilon_t \tag{8}$$

$$\text{Model D}: \Delta y_t = \mu + \beta t + \gamma_1 \sin\left(\frac{2\pi kt}{T}\right) + \gamma_2 \cos\left(\frac{2\pi kt}{T}\right) + \delta DU_t + \theta D(T_B)_t + \rho y_{t-1} + \sum_{i=1}^{p} c_i \Delta y_{t-i} + \varepsilon_t \tag{9}$$

Here, Model A is the ADF model that ignores structural breaks and nonlinearity, Model B is the Fourier ADF (FADF) model that takes into account nonlinearity, Model C is the ADF-SB model that takes into account structural breaks, and Model D is the FADF-SB model that takes into account both structural breaks and nonlinearity. The FADF-SB model proposed by Furuoka (2017) is sensitive to both break location and frequency (k). k denotes the number of Fourier frequencies and its value is determined as the value that yields the smallest sum of residual squares. β is the slope parameter of the trend, γ is the slope parameter for trigonometric or Fourier terms, t is the deterministic trend, T is the number of observations, $\pi = 3.1416$, and δ is the slope parameter for the structural break dummy. $DU_t = 1$ if $t > TB$, otherwise $DU_t = 0$. TB is the break point when a structural break occurs, θ is the slope parameter for the single break dummy. On the other hand, if $t = TB$, $D(T_B)_t = 1$, otherwise $D(T_B)_t = 0$ (Furuoka, 2017).

4.2.4. Augmented autoregressive distributed lag (A-ARDL) method

The ARDL approach, which is the starting point of the Augmented ARDL approach and developed by Pesaran et al. (2001), has been preferred by many researchers so far because it allows independent variables to be stationary of different degrees ((I(0) or I(1)) and can be used for small samples. However, the ARDL method also has many strict assumptions such as the dependent variable must have a unit root, exogeneity of explanatory variables, and the existence of degenerate states. Violation of these strict assumptions may make the results equally misleading (Sam et al., 2019). However, unlike the ARDL method developed by Pesaran et al. (2001), the A-ARDL method developed by McNown et al. (2018) and Sam et al. (2019) also takes into account the I (0) status of the dependent variable. In other words, the endogeneity problem and the requirement that the dependent variable is I(1) are eliminated in the A-ARDL model (Pata and Caglar, 2021; Turna, 2023). The adaptation of the A-ARDL model used in the analysis to the variables is shown below.

$$\Delta LAGDP_t = \alpha_0 + \beta_0 LAGDP_{t-1} + \beta_1 LAGAR_{t-1} + \beta_2 LCO2_{t-1} + \beta_3 LMINT_{t-1} + \beta_4 LTCMGT_{t-1} + \sum_{i=0}^{p-1} c_{0,i}\Delta LAGDP_{t-i} + \sum_{j=1}^{q_{j-1}} c_j L\Delta AGAR_{t-i} + \sum_{j=1}^{q_{j-1}} c_j \Delta LCO2_{t-i} + \sum_{j=1}^{q_{j-1}} c_j \Delta LMINT_{t-i} + \sum_{j=1}^{q_{j-1}} c_j \Delta LTCMGT_{t-i} + d_1\Delta LAGAR_t + d_2\Delta LCO2_t + d_3\Delta LMINT_t + d_4\Delta LTCMGT_t + \varepsilon_t \tag{10}$$

In Equation (10), ε_t is the error term, Δ is the first difference operator, variables expressed in summation terms refer to the short-run relationship and variables including the coefficient β refer to the long-run relationship. L stands for the natural logarithm. In this framework, the A-ARDL model can test the long-run cointegration relationship between the variables based on an unconstrained error correction model (ECM) as in the ARDL model developed by Pesaran et al. (2001). Therefore, in the ARDL bounds test model used to test these hypotheses, Pesaran et al. (2001) proposed a general upper bound and lower bound determined using the F statistic. In this framework, if the F statistic value obtained from the ARDL bounds test model is greater than the upper critical value, it is stated that there is a cointegration relationship between the variables. However, the following steps should be followed in the A-ARDL model;

1. Step: A bound test (F_{all}) should be performed for all lagged values $H_0 : \beta_0 = \beta_1 = \beta_2 = \beta_3 = 0$.[1]
2. Step: The t-test should be performed only for the lagged dependent variable $H_0 : \beta_0 = 0$.[2]
3. Step: F test is performed only for lagged independent variables $H_0 : \beta_1 = \beta_2 = \beta_3 = 0$.[3]

In order to speak of a cointegration relationship, all three hypotheses must be rejected. Otherwise, cointegration relationship cannot be mentioned. Contrary to the ARDL test developed by Pesaran et al. (2001), t-test is applied to the lagged value of the dependent variable in the A-ARDL model. In the ARDL model, the F statistic is significant only because the lagged value of the dependent variable is significant. However, this indicates that the dependent variable is I(0). This means that a false cointegration relationship is estimated. Hence, if an additional t-test on the lagged value of the independent variable is significant, this error can be eliminated (Sam et al., 2019).

5. Empirical results and discussions

This section discusses the selection of relevant explanatory variables to include in the econometric model. Here, we adopt two approaches: first partial and semi-partial correlation and second BMA. Examining the information presented in Table 3, it is clear that the partial and semi-partial correlations between LCO2, LAGAR, LPREC and LAGDP are different from zero. The partial and semi-partial correlations between the other variables and LAGDP are not different from zero. Therefore, LCO2, LAGAR and LPREC can be selected among the 10 candidate explanatory variables based on the partial and semi-partial correlation coefficients. The signs of the correlation coefficients indicate a negative relationship between these variables and LAGDP.

In addition, our objective is to estimate the importance of the candidate explanatory variables for the determination of AGDP in this section. Therefore, we apply BMA to rank all candidate explanatory variables. The summary results of the BMA model are shown in Table 4.

Table 4 indicates that we used 53 annual observations corresponding to the period between 1970 and 2022, and p = 10 explanatory variables for the analysis.Model enumeration was used and all possible 2ˆ10 = 1024 models were visited. Among these models, 82 models contribute at least 0.9 to the cumulative posterior model probability (CPMP). The average model size is 4.308, indicating that on average the models

[1] Critical values for comparing the F test statistic are obtained from Narayan (2005).

[2] The critical values for comparing the t-test statistics are obtained from Pesaran et al. (2001).

[3] Critical values for comparing the F test statistic are obtained from Sam et al. (2019).

Table 3
Partial and semipartial correlation analysis.

Variable	Partial correlation	Semipartial correlation	Partial correlation^2	Semipartial correlation^2	P value
LAH	0.1961	0.0275	0.0385	0.0008	0.2020
LCO2	−0.9482	−0.4107	0.8990	0.1687	0.0000
LAGAR	−0.4415	−0.0677	0.1949	0.0046	0.0027
LPREC	−0.2786	−0.0399	0.0776	0.0016	0.0671
LMAXT	−0.0371	−0.051	0.0014	0.0000	0.8112
LMINT	0.2145	0.0302	0.0460	0.0009	0.1621
LTEMP	−0.0189	−0.0026	0.0004	0.0000	0.9030
LNDWSC	0.1951	0.0274	0.0381	0.0007	0.2044
LFCMGT	−0.0535	−0.0074	0.0029	0.0001	0.7301
LTCMGT	−0.1494	−0.0208	0.0223	0.0004	0.3331

Table 4
Bayesian model averaging results.

Varibales	Mean	Std.Dev	PIP
LCO2	−8.1666	0.3463	1
LAGAR	−0.9586	0.3563	0.9659
LMINT	0.9921	0.9986	0.6159
LTCMGT	−1.9830	1.9429	0.5880
LFCMGT	−0.4225	0.9672	0.2522
LAH	0.4053	1.0421	0.2289
LTEMP	0.1890	1.4443	0.2130
LPREC	−0.0479	0.1373	0.1870
LMAXT	−0.0372	1.0921	0.1348
LNDWSC	0.0061	0.0273	0.1228

Note: N of obs = 53 Number of predictors = 10, N of models = 1024, For CAMP≥0.9 = 82, Mean model size = 4.308, Models: Beta-binomial(1,1); Cons.: Noninformative; Coef.: Zellner's g. g: Benchmark; g = 100; Shrinkage, g/(1 + g) = 0.9901, $\overline{\sigma}^2$ = **0.013**

contain about four explanatory variables. We used the same non-informative priors proportional to 1/σ2 for the constant and error variance and a Zellner g-prior for the regression coefficients. However, there are various options for model and parameter g-priorities. In this study, however, we use the Beta-binomial (1, 1) model prior, which assigns equal probability for each model dimension. The default g-prior is the Benchmark prior following (Fernandez et al., 2001) with a fixed value for g = max(n, p2) = max(53, 1024) = 1024. This corresponds to a shrinkage parameter δ = g/(1 + g) = 0.9901, where δ = 1 means no shrinkage and δ = 0 means full shrinkage. In this study, we assumed a priori that there is very little shrinkage. The posterior mean estimates of the error variance have mean $\sigma^2 = 0.019$. Carbon emissions, agricultural cropland, five and ten cm soil surface temperature, precipitation and maximum temperature have negative posterior mean coefficients, while minimum temperature, average humidity, average temperature, and number of snow-covered days have positive posterior mean coefficients. The signs of the posterior mean coefficients suggest how the variables affect the dependent variables. Table 4 also presents the posterior means of the coefficients, estimates of their standard deviations and estimated posterior inclusion probabilities (PIPs) for each candidate explanatory variables. If the PIP value is greater than 0.50, it means that the candidate variable will be included in the model. As a result, it was decided to include carbon emission, arable agricultural area, minimum temperature and ten cm soil surface temperature in the model. The remaining candidate variables will not be included in the model since their PIP value is less than 0.5.

The detailed information of the BMA model is generated in Fig. 4 using the variable inclusion map in addition to Table 4. The variable inclusion map shows the top 100 models out of 1024 visited. The models are ranked according to their PMPs (highest to lowest) and their CPMPs are shown on the x-axis. All 10 explanatory variables are shown on the y-axis. Each model and variable pair is represented by a bar with a width proportional to the PMP of the model. The bar is colored blue if a predictor is included in the model with a positive coefficient, red if a predictor is included in the model with a negative coefficient, and gray if a

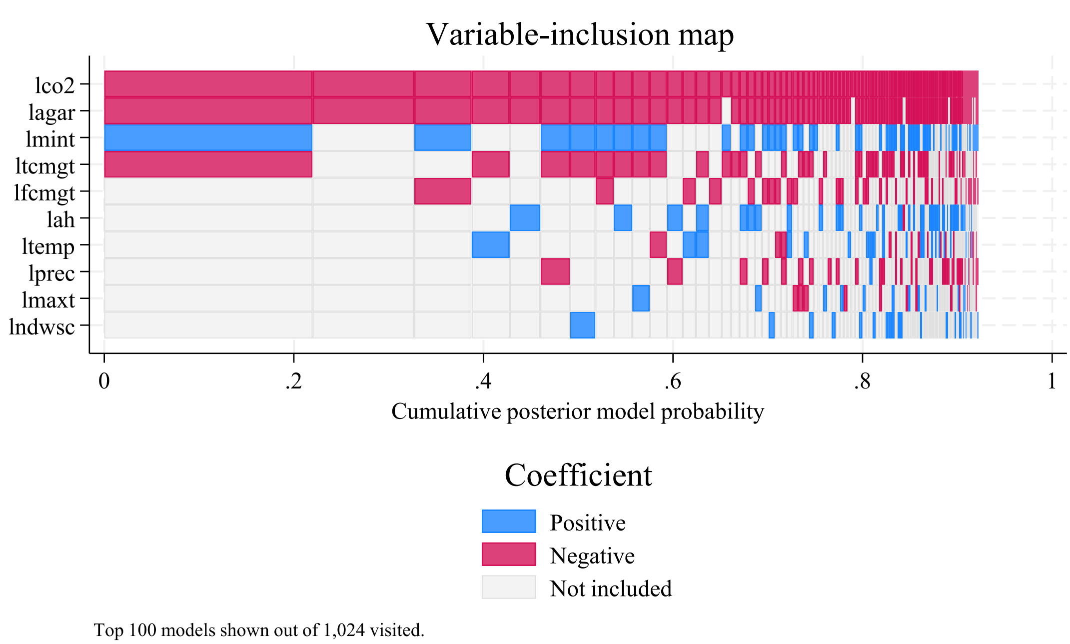

Fig. 4. Variable-inclusion map.

Table 5
Model ranking.

	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
LCO2	✓	✓	✓	✓	✓
LMINT	✓		✓		
LTCMGT	✓			✓	
LAGAR	✓	✓	✓	✓	✓
LFCMGT			✓		
LTEMP				✓	
LAH					✓

predictor is not included in the model. In our example, since all models are included in the map, the plotted range of the CPMP x-axis is between 0 and 1.

Although the PIPs values given in Table 4 and the information presented in the Variable-inclusion map are fully consistent with the partial and semi-partial correlation coefficients given in Table 3 in terms of sign, they do not match exactly in terms of candidate variable selection. Namely, CO2, AGAR, PREC variables should be selected based on the information presented in Table 3, while CO2, AGAR, MINT and TCMGT variables should be included in the model based on the information presented in Table 4 and Fig. 4. Since our objective here is to minimize model uncertainty, we use the variables selected by the BMA approach. The BMA approach is more reliable and robust because it evaluates all possible models and calculates the fit of each model to the data with a certain probability.

The results in Table 5 present the top 5 models out of 1024 models visited by the BMA approach. The ranking shows that the model with the candidate explanatory variables CO2, AGAR, MINT and TCMGT among the 10 candidate explanatory variables would be the best model. It should be noted that CO2 and AGAR variables were included in the model for the top 5 alternatives (Rank 1- Rank 5). This result implies that CO2 and AGAR are very important determinants of AGDP. In light of all this evidence, equation (11) can be written for the determinants of AGDP.

$$AGDP_t = f(AGAR_t, CO2_t, MINT_t, TCMGT_t) \tag{11}$$

Before estimating the model, descriptive statistics of the variables in the model given in equation (11) are reported in Table 6. According to the information presented in Table 6, the share of agricultural products in GDP was 15.56 % on average, and the average area under cultivation was 17116 mln hectares. The average CO2 per capita was 367.84 kt, while the minimum average temperature was 7.88 °C and the average temperature above 10 cm of soil was 15.80 °C. When the skewness values are analyzed, it is seen that the skewness values of all variables are positive. This shows that the distributions of the variables are skewed to the right compared to the normal distribution. In other words, the majority (more than 50 %) of the values in the period analyzed in all variables took smaller values than the average value. However, the fact that the skewness values do not differ sharply from zero indicates that the degree of skewness is not high. Examining the CV statistic values, the variable with the highest change in the relevant period was AGDP and the variable with the lowest change was TCMGT. Considering the probability values of the Jarque-Bera normality test, we can say that AGAR, CO2, MINT and TCMGT variables have normal distribution at 5 % significance level and AGDP variable has normal distribution at 1 % significance level. In addition to the summary statistics in Table 6, we also examined the specific years corresponding to the peaks and troughs of each variable. AGDP (Share of agricultural GDP) peaked in 1975, largely due to favorable climatic conditions and a government-led rural development program. The lowest value was recorded in 2022, reflecting the sector's long-term decline in economic contribution. AGAR (Agricultural cultivated area) reached its highest point in 2010, likely due to the expansion of irrigation investments, while the lowest level occurred in 1971, when mechanization and land fragmentation limited arable capacity. CO2 emissions peaked in 2019 as a result of increased industrial activity, while the lowest level was in 1970, the initial year of the sample and a period of low economic development. Minimum average temperature (MINT) was highest in 2010, in line with global warming trends, and lowest in 1985, a year marked by unusually cold winters in Türkiye. 10 cm ground temperature (TCMGT) was highest in 2018, likely due to extreme summer conditions, and lowest in 1992, during a relatively cool climatic phase. These peaks and troughs correspond to known climatic or economic events, and reflect structural shifts in Türkiye's agriculture-environment interactions over time.

Moreover, considering that the variables are normally distributed, Pearson correlation coefficient was calculated and presented in Fig. 5 to have information about the direction and strength of the relationship between the variables. In addition, the scatter plots between the variables and the kernel distributions of the variables are also presented in Fig. 5.

Fig. 5 shows that the relationship between AGDP and AGAR is positive but statistically insignificant, whereas the relationship between AGDP and other variables is negative, strong and statistically significant. Since the descriptive statistics, correlation coefficient, scatter plots and kernel distributions of the variables are insufficient to see the dynamics (increase/decrease) of the variables over time, time graphs of the variables were plotted and presented in Fig. 6.

Fig. 6 shows that, except for the LCO2 variable, the dynamics (increase/decrease) of the other variables over time are more clearly observed. Positive trend structure is not very clear in the LMINT and LTCMGT variables, although a positive trend is clearly visible in the LCO2 variable. On the contrary, a negative trend is observed in LAGDP and LAGAR variables. However, while the negative linear trend structure is more dominant in LAGDP, the negative quadratic (concave) trend is more dominant in LAGAR. It may be misleading to conclude about the degree of stationarity of the variables by considering the time graphs of the variables. For this reason, the Fourier ADF-SB test developed by Furuoka (2017) was used to determine the degree of stationarity of the variables and the results obtained are presented in Table 7.

In the light of the information presented in Table 7, it is concluded that LMINT and LTCMGT variables are stationary at level, while LAGDP, LCO2 and LAGAR variables are stationary at first difference. Consequently, the stationarity levels of the variables are different. In addition to the fact that the dependent variable is I(1), having a break allows us to decide that the A-ARDL method is appropriate for investigating the cointegration relationship between these variables. Hence, the A-ARDL method was applied and the results are presented in Table 8.

Based on the results in Table 8, we can say that the preferred model is based on the case of unrestected intercept and no trends (CASE III). Since the F, t and Findependent test statistics are greater than the Pesaran et al. (2001), Narayan (2005) and Sam (2019) critical values respectively, the null hypothesis of no cointegration between variables is rejected. Therefore, A-ARDL method proves the existence of cointegration relationship between variables. Normality, autocorrelation and heteroskedasticity assumptions as well as specification and stability tests

Table 6
Descriptive statistics.

DS	AGDP	AGAR	CO2	MINT	TCMGT
Mean	15.564	17116	367.84	7.8863	15.804
Median	14.461	16945	363.88	7.7.000	15.800
Maximum	36.002	19036	418.56	10.000	17.600
Minimum	5.5431	15398	327.46	6.0000	14.300
Std. Dev.	9.2866	1198.7	26.797	0.8158	0.6933
Skewness	0.8634	0.1501	0.2707	0.4103	0.1295
CV•	0.5967	0.0700	0.0728	0.1035	0.0439
Kurtosis	2.5633	1.5768	1.9166	3.0288	2.7664
Jarque-Bera	6.7420	4.4956	3.1174	1.4324	0.2585
Probability	0.0343	0.1056	0.2104	0.4886	0.8787
Observations	53	53	53	53	53

CV: Coefficient of Variation, DS: Descriptive Statistics.

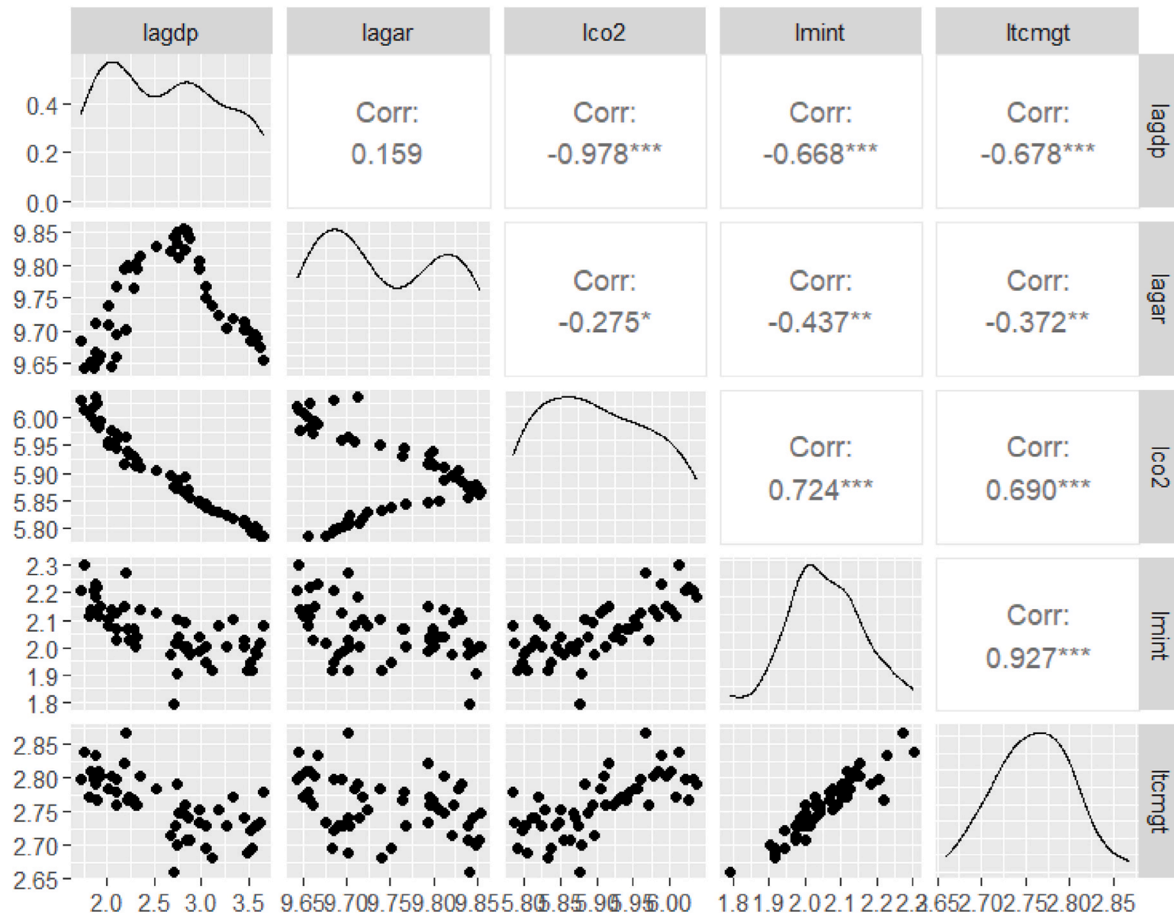

Fig. 5. Correlation matric, scatter plot and kernel distribution of variabes.

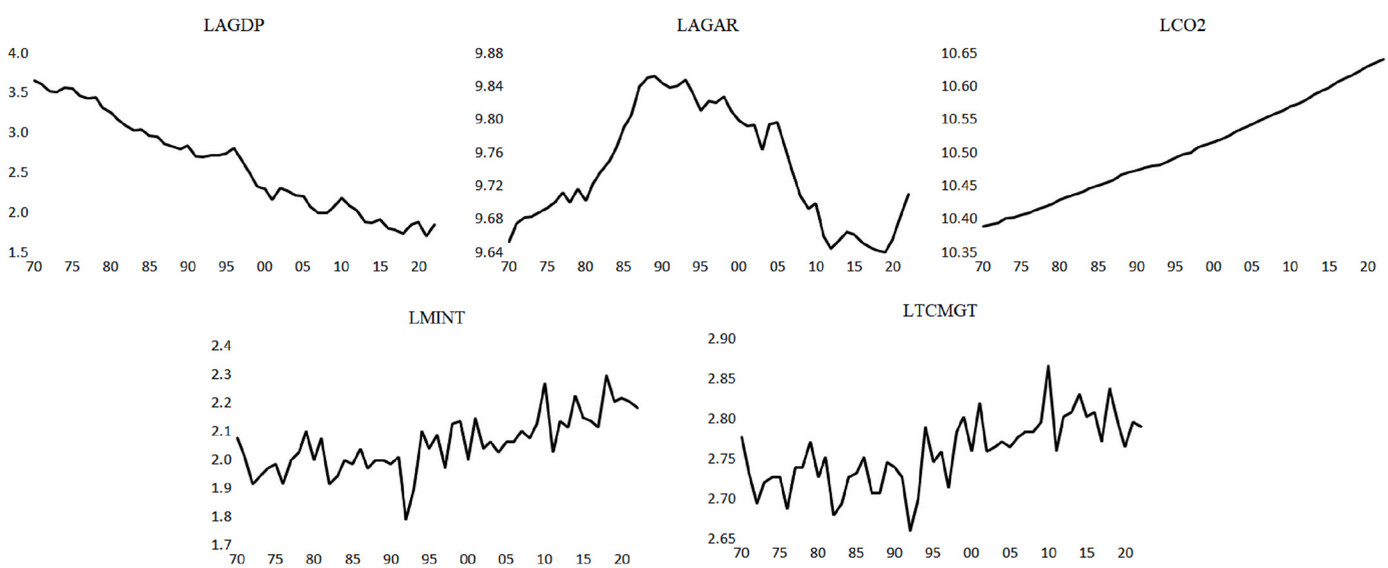

Fig. 6. Time series graphics of variables.

were conducted on the residuals obtained from the estimated A-ARDL(3, 0,4,2,2) model. According to the test results, the residuals are normally distributed and there are no autocorrelation and heteroskedasticity. According to Ramsey's RESET test, there is no specification error in the model. Additionally, the model parameters are stable according to the CUSUM and CUSUM SQ tests given in Fig. 7.

Since the estimated model satisfied all the necessary assumptions, the long-run coefficients between the variables were estimated by CCR, DOLS and FMOLS methods and the results were presented in Table 9.

Long-run equation was estimated applying CCR, DOLS and FMOLS methods, but DOLS estimators were considered the best estimators according to the highest $\overline{R}^2$ and the smallest standart error of regression criterion. However, comparing DOLS estimators with other estimators,

Table 7
FADF-SB results.

Variables	Deterministic Component	Test Type	F stat	TV	Conclusion
LAGDP	C&T	FADF-SB, k = 1, l = 0 BT1996, λ = 0.51	3.866	−3.710	I(1)
LAGAR	C&T	FADF-SB, k = 1, l = 0 BT = 2004, λ = 0.66	17.92	−2.147	I(1)
LCO2	C&T	FADF-SB, k = 1, l = 0 BT = 1993, λ = 0.45	5.558	−3.379	I(1)
LMINT	C&T	FADF-SB, k = 1, l = 0 BT = 1993, λ = 0.45	8.742***	−8.787***	I(0)
LTCMGT	C&T	FADF-SB, k = 1, l = 0 BT = 1992, λ = 0.43	8.579***	−7.811***	I(0)

Critical values for λ = 0.40–0.59 are −5.44, −4.70, −4.36 at 1 %, 5 % and 10 % significance levels, respectively.
Critical values for λ = 0.60–0.79 are −5.39, −4.70, −4.36 at 1 %, 5 % and 10 % significance levels. respectively.
C&T refer to Constant and Trend.
TV refer to Test Value.

it is clear that there is not a significant difference between them.

The estimation results of DOLS revealed that CO2 emissions have a negative and significant impact on AGDP. This shows that a 1 % rise in CO2 emissions results in a 7.885 % fall in AGDP. This negative finding can be interpreted as increasing carbon emissions not only having negative effects on the climate but also causing productivity losses in agricultural production. It reveals that the increase in CO2 levels increases the frequency of disasters such as droughts or floods by increasing extreme weather events, which in turn reduces productivity in agricultural education, especially in sensitive production structures. It can be said that especially high CO2 emissions reduce agricultural production through indirect factors such as making it difficult to use water resources efficiently through climate change and instability in weather conditions, shortening the growth periods of plants, or facilitating the spread of harmful insects and diseases. Furthermore, when we look at Türkiye specifically, it is seen that the emissions released into the environment with the increasing industrialization and urbanization in recent years have increased the pressure on the agricultural sector. In 1990, Türkiye's CO2 emissions were 155.16 million tons of CO2 equivalent, and they have consistently risen to 433.75 million tons of CO2 equivalent by 2022 (EDGAR, 2024). The portion of the value added by agricultural sector to Türkiye's GDP has decreased, reaching a record low of 5.8 percent in 2022 (Statista, 2024). This situation may limit the production potential of traditional agricultural regions in the medium and long term and reduce the importance of agriculture in the country's economy. Moreover, Amponsah et al. (2015) found a negative effect of CO2 emissions on agriculture production in tha case of Ghana.

Additionally, the estimation results revealed that a 1 % increase in the AGAR causes a 1.196 % decline in AGDP. However, this finding shows that the expansion of unproductive land or the deterioration in the quality of existing lands may not be effective in increasing production. The fact that the expansion of agricultural lands does not increase productivity can be explained by reasons such as industrial and urban development reducing the most productive lands that can be allocated to agriculture, resulting in the expanded agricultural lands being only marginal lands. This could also be because of things like the poor quality of the soil in newly opened or expanded areas, a lack of good irrigation systems, bad weather, or farmers' limitations on the technology and inputs they can use. Due to qualitative shortcomings, increasing the amount of land does not lead to the expected rise in productivity and cannot contribute to the rise in production. As a result, agriculture's role in the economy decreases. Climate change and soil degradation in Türkiye limit the productivity potential of expanded agricultural lands. Furthermore, in recent years, the agricultural sector has often been pushed to lower quality lands as a result of the competition in land use between sectors such as industry, tourism and housing. As a result, the fact that land expansion does not result in an effective increase in production also reduces the share of agriculture in the economy.

We also found that, A 1.699 % rise in AGDP is associated with a 1 % rise in the minimum temperature. This positive impact of minimum temperature shows that it may have positive effects on agricultural activities, especially in colder regions. It can be said that increasing the minimum temperature during the development periods of plants sensitive to cold conditions extends the growing season by reducing frost damage, which in turn increases the production amount. Therefore, the literature indicates that temperature increases in temperate climate regions during the climate change process may bring about increases in yield in certain types of products. Therefore, regions with cold climate conditions, especially in Türkiye, such as Eastern Anatolia or the high-altitude regions of the Black Sea, may benefit relatively more from increasing the minimum temperature. In addition, our findings align with the results of Ali et al. (2017) for Pakistan.

Moreover, a 1 % increase in the temperature 10 cm above the top of the ground leads to a 4.799 % decrease in the share of agricultural production in GDP. This result shows that soil warming has negative effects on plant development, especially by negatively affecting root development, soil moisture, and microorganism balance. In addition, extreme temperature conditions can reduce yield by stressing sensitive

Table 8
A-ARDL results.

	Model	*Lag Order*	*Dummy*	*F*	*t*	*$F_{independent}$*	Cointegration
	Case 3	3,0,4,2,2	1996	**7.0767***	**−4.6181***	6.0234**	✓
KD	Pesaran et al. (2001)		Narayan (2005)		**Sam(2019)**		
	Lower limit	Upper limit	Lower limit	Upper limit	Lower limit	Upper limit	
1 %	3.74	5.06	4.24	5.73	3.75	6.19	
5 %	2.86	4.01	3.06	4.33	2.55	4.51	
10 %	2.45	3.52	2.58	3.71	2.06	3.72	
Diagnostic Check							
Model	*R^2*	*F-stat*	*JB*	*BG-LM*	*White*	*R-R*	*Stability*
Model 3	**0.9879**	**246.97***	**0.4485**	**0.9250**	**0.7621**	2.6339	✓

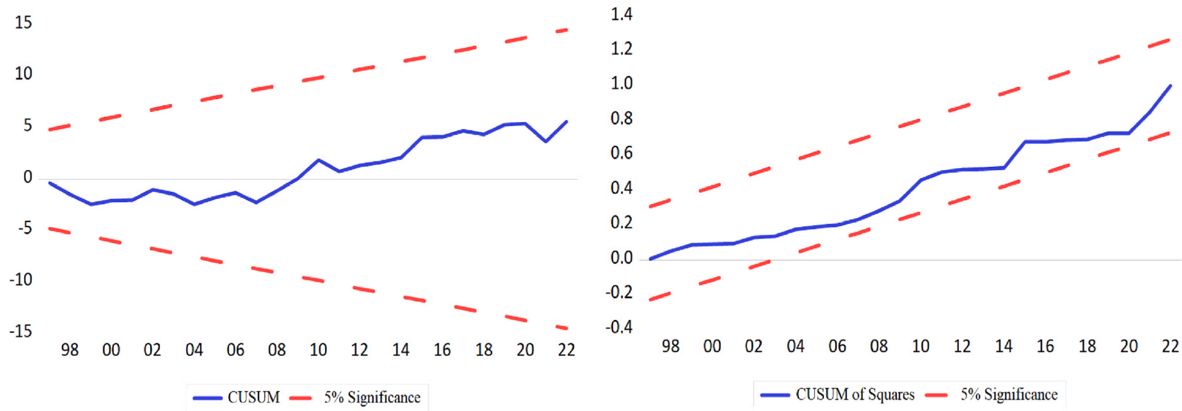

Fig. 7. Stability test results.

Table 9
Long-run estimation results.

	CCR	DOLS	FMOLS	VIF	Tolerance
Variables	Coefficients				
Constant	106.08***	106.93***	105.83***	–	–
D1996	0.2504*	0.2711**	0.2546**	–	–
LCO2	−8.0405***	−7.8858***	−8.1267***	2.96	0.34
LAGAR	−1.0707***	−1.1963***	−1.0244***	1.85	0.54
LMINT	1.5889***	1.6994*	1.6043***	5.79	0.17
LTCMGT	−4.3164***	−4.7990**	−4.0442***	5.09	0.20
$\overline{R}^2$	0.9755	0.9789	0.9762		
SER	0.0933	0.0844	0.0920		

plants. This situation shows that excessive temperature increases, especially during critical periods, can have a strong negative effect on yield. It is also emphasized in the literature that the increase in surface temperature causes stress conditions by increasing water loss in plants, which reduces yield and product quality. As a result, the increase in surface temperature puts pressure on agricultural production in the long term, causing its share in GDP to decrease.

Finally, variance inflation factor (VIF) statistics and Tolerance values were calculated to determine whether there is multicollinearity among the explanatory variables in the model. Since the VIF statistics for CO2 and AGAR variables are less than 5, these variables do not cause multicollinearity. The VIF statistics for MINT and TCMGT variables are greater than 5 but less than 10, so we can state that there is no significant problem with multicollinearity. These results are also reflected in the correlation matrix presented in Fig. 2. Namely, the correlation coefficient between MINT and TCMGT was 0.927. In addition, since the tolerance values are not very close to zero, it is possible to state that there is no multicollinearity problem in the model.

6. Conclusions

The relationship between climate change and agricultural production in Türkiye—one of the nations most impacted by climate change because of its geographic location—is examined in this research during 1970–2022. In order to determine which climatic factors have the greatest impact on agricultural production, a number of variables that are believed to affect agricultural production based on theory and previous studies were excluded from the model and the model specification was determined using the Bayesian Model Averaging (BMA) approach. This model has high specificity in this regard. Based on BMA, we determined that the model specification, which includes AGDP, CO2, AGAR, MINT, and TCMGT variables, is the best model. The A-ARDL cointegration test demonstrated the existence of cointegration relationships between the variables. Finally, the long-term effect of independent variables on agricultural production was examined using the CCR, DOLS, and FMOLS estimators. The estimation results revealed that CO2, AGAR, and TCMGT have a negative impact on AGDP. On the other hand, MINT has a negative effect on AGDP. The results obtained are observed to be consistent with predictions.

Based on obtained findings, the key policy recommendations are following: i) The contemporary irrigation methods should be promoted to enhance water use efficiency in response to increasing soil and air temperatures. In addition, it is better to use strategic land-use planning that prevents over-expansion of agricultural zones on marginal or ecologically sensitive lands. ii) It is necessary to establish early warning systems to alleviate hazards linked to severe meteorological phenomena such as heatwaves, droughts. iii) The policymakers should develop specific measures to reduce carbon dioxide emissions, particularly in high-emission sectors like energy, industry, and transportation, or promote carbon capture measures that include reforestation, afforestation, and soil carbon sequestration in agricultural areas. Furtherfore, Turkish policymakers should establish carbon trading mechanisms or incentives for the application of low-carbon agricultural techniques, such as minimal tillage and precision agriculture. iv) It is better to offer farmers instruction on climate-smart agriculture and the use of modern technology to enhance production amid shifting climatic circumstances. Also, it is necessary to promote the cultivation of diverse crop varieties that exhibit resilience to elevated soil temperatures and variable precipitation patterns. v) Making research and development investments may create crop types that are resilient to temperature fluctuations without sacrificing yield. vi) The encouraging collaborations between research organizations, government agencies, and local communities may promote information transfer and assist farmers in their adaptation procedures. Therefore, by implementing coordinated and proactive measures, Turkish authorities can protect agricultural output and enhance economic growth in the face of climate change threats.

In spite of its contributions, there are some limitations to this study, which should be acknowledged. First, analysis is limited to a single country (only Türkiye), which could constrain generalizability for other world regions with varied climatic and economic conditions. Second, even though Bayesian Model Averaging (BMA) and augmented ARDL (A-ARDL) approaches were utilized for increasing robustness, accuracy for the model still depends on the quality and completeness of historical climate and agricultural data. Data constraints, particularly for previous years, could introduce errors or bias for estimation of long-term effects. Third, the analysis is largely confined to macro-level effects of climatic variables on agricultural production, which could ignore micro-level variations at a farm level. Further research is needed, which could widen the scope by using data at a farm level and looking at cross-country comparisons for wider generalizability.

CRediT authorship contribution statement

Ahmet Emrah Tayyar: Writing – review & editing, Writing – original draft, Investigation, Data curation, Conceptualization. **Nijat Gasim:** Writing – review & editing, Writing – original draft, Resources, Methodology, Investigation, Data curation. **Ömer Faruk Biçen:** Writing – review & editing, Writing – original draft, Visualization, Investigation, Conceptualization. **Shahriyar Mukhtarov:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Conceptualization.

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Data availability

Data will be made available on request.

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