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The impact of climate policy uncertainty on agricultural investments

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Abstract

Purpose: The agricultural sector is strategically important for sustainable development and food security. However, climate change and the increasing physical and political uncertainties that come with it put investments in this sector at risk. This study examines the relationship between climate policy uncertainty and agricultural investments in the USA from 1995-2022.

Design/Methodology/Approach: The nonlinear ARDL method and asymmetric causality test are used to analyze the relationships between climate policy uncertainty and agricultural investments. Nonlinear methods allow us to measure asymmetric effects on the dependent variable by evaluating the positive and negative changes of the explanatory variables separately.

Findings: According to the NARDL model results, increases in climate policy uncertainty reduce agricultural investments in the long run. The asymmetric causality test provides additional evidence for the asymmetric relationships identified by the NARDL model. There is a statistically significant asymmetric causality from the positive shock of climate policy uncertainty to the negative shock of agricultural investments.

Originality/Value: This study fills the gap in the literature by examining the impact of climate policy uncertainty on investments in the agricultural sector. This provides a new perspective to understand the long-term consequences of this relationship in a highly climate-sensitive area such as the agricultural sector.

Keywords: Agricultural investments, agriculture, climate change, climate policy uncertainty, NARDL

İklim politikası belirsizliğinin tarımsal yatırımlara etkisi

Özet

Amaç: Tarım sektörü hem sürdürülebilir kalkınma hem de gıda güvenliği açısından stratejik bir öneme sahiptir. Ancak, iklim değişikliği ve buna bağlı olarak artan fiziksel ve politik belirsizlikler, bu sektördeki yatırımları riske atmaktadır. Bu çalışmanın amacı, ABD'de iklim politikası belirsizliği ile tarımsal yatırımlar arasındaki ilişkiyi 1995-2022 dönemi için incelemektir.

Tasarım/Metodoloji/Yaklaşım: İklim politikası belirsizliği ile tarımsal yatırımlar arasındaki ilişkileri analiz etmek için doğrusal olmayan ARDL yöntemi ve asimetrik nedensellik testi kullanılmaktadır. Nonlinear yöntemler, açıklayıcı değişkenlerin pozitif ve negatif değişimlerini ayrı ayrı değerlendirerek bağımlı değişken üzerindeki asimetrik etkileri ölçmeyi sağlamaktadır.

Bulgular: NARDL modelinin sonuçlarına göre, iklim politikası belirsizliğindeki artışlar uzun dönemde tarımsal yatırımları azaltmaktadır. Asimetrik nedensellik testi, NARDL modeli tarafından tanımlanan asimetrik ilişkiler için ek kanıt sağlamaktadır. İklim politikası belirsizliğinin pozitif şokundan tarımsal yatırımların negatif şokuna doğru istatistiksel olarak anlamlı bir asimetrik nedensellik vardır.

Özgünlük/Değer: Çalışma, iklim politikası belirsizliğinin yatırımlar üzerindeki etkisini tarım sektörü açısından inceleyerek literatürdeki boşluğu doldurmaktadır. Bu, tarım sektörü gibi iklime oldukça duyarlı bir alanda, söz konusu ilişkinin uzun vadeli sonuçlarını anlamaya yönelik yeni bir perspektif sağlamaktadır.

Anahtar kelimeler: Tarımsal yatırımlar, tarım, iklim değişikliği, iklim politikası belirsizliği, NARDL

INTRODUCTION

The impacts of climate change are many and varied. Changes in phenomena such as temperature, precipitation, cloud cover, wind direction and speed, and alkalinity directly affect living organisms and ecosystems. These impacts are further affected by other ecological interactions (Tol, 2019). Carney (2015) reports three main risks related to climate change: (i) physical risks, (ii) liability risks, and (iii) transition risks. The first is extreme weather events resulting from the gradual global warming change. The second is the financial risks that may arise when parties harmed by climate change seek compensation from those responsible. The third is the possible impacts of the transition to a low-carbon economy. The latter is actually a risk that creates uncertainty in climate policy. Emphasizing that climate change is one of the biggest global challenges, Feyen et al. (2020) state that if sufficient measures are not taken to reduce emissions, it is inevitable that the negative climate change effects will accelerate and reach an uncontrollable size. In addition, Nordhaus's 'climate casino' analogy is even more tragic. Nordhaus (2020) argues that the two extreme policies of stopping global warming by banning all fossil fuels or taking no action for a long time are irrational and even a reckless gamble. According to him, 'good policy' must lie somewhere between these policies, the first of which will destroy the economy and the second of which will destroy the world. This critical choice between the two extremes is the main problem that causes uncertainty in climate policies. Taking no action is the worst-case scenario for everyone. It is not the interest of this study. So, what should an active climate policy be like? Should a carbon tax be levied on polluters? Should the transition to renewable energy technologies be made mandatory? Should products such as electric vehicles and green financing be encouraged? Will commitments made to the Paris Climate Agreement be fulfilled? Would countries really want to compromise their economic growth? How much will each country fight climate change? Will laws support this fight? These questions create uncertainty about the incentives and sanctions for combating climate change and adaptation policies. This uncertainty in climate policies is likely to affect investments (Hoang, 2022; Li and Su, 2022; Ren et al., 2022; Zhang et al., 2023; Zhao et al., 2025), carbon emissions (Dinç, 2022; Zeng et al., 2022; Hashmi et al., 2023; Tian and Li, 2023; Kisswani et al., 2024), stock markets (Chan and Malik, 2022; He and Zhang, 2022; Chen et al., 2023; Lv and Li, 2023), oil prices (He and Zhang, 2022; Salisu et al., 2023; Zhou et al., 2023) and many other related macroeconomic variables. The Network for Greening the Financial System (NGFS) (2020) expresses that climate change's physical and transition risks can affect almost all macroeconomic variables through different channels, from production to consumption, investment to productivity, labor to wages, international trade to exchange rates and inflation.

The impact of climate policy uncertainty on investment (Neuhoff, 2007; Fuss et al., 2008) is not a new agenda. Uncertainty in climate policy stems from uncertainties in climate change's science, economics, and politics. These uncertainties are particularly influential when investing in energy markets because deciding to control or not control emissions in a sector where policy regulation is aimed poses a vital risk to potential investments (Fuss et al., 2008). Feyen et al. (2020) and Fried et al. (2021) indicate that active policies against climate risks will affect the productivity of existing investments and new investment decisions. NGFS (2020) explained the effects of climate change on investments according to the type of climate risk as follows:

i. *Extreme weather events:* Increased uncertainty, volatility and destruction of valuable capital stock reduce investments. Moving away from high-productivity investments may reduce investments.
ii. *Gradual warming:* Investments shift towards climate adaptation technologies.
iii. *Transition risk:* Investments are low due to uncertainty in future policies and increasing idle assets.

The above relationships explained theoretically by NGFS (2020) are empirically proven by studies such as Ren et al. (2022), Zhang et al. (2023), Abdulai et al. (2024), and Zhao et al. (2025). In other words, these studies have identified an adverse relationship between climate policy uncertainty and investments. In this context, it is thought that the agricultural sector requires special attention because it stands out as one of the most sensitive sectors to climate change. Pardey and Alston (2020) explain the drivers of productivity in the United States of America (USA) agriculture, and they also touch on the role of climate change in the structural transformation of agriculture. Anton et al. (2013) state that the effects of climate change on agricultural product productivity will determine adaptation strategies by increasing the demand for agricultural risk management tools. Zhou et al. (2022) also report that climate shocks adversely affect farmers' productive investments by increasing the uncertainty in agricultural production. Heumesser et al. (2012), one of the studies that analyze the uncertainty created by the physical risks of climate more specifically, examined the optimal investment strategies of saving or rain-fed irrigation systems. In another related study, Ouattara et al. (2018) investigate the soil conservation decisions of farmers exposed to the negative effects of climate change. Today, many negative factors triggered by climate change, such as temperature increases, changes in the amount and regime of precipitation, increased frequency and severity of extreme weather events, desertification, and sea level rise continue to affect agricultural activities on a global scale. In addition, neoliberal policies prioritizing the industry and services sector worldwide have made agriculture a very fragile (Adaman et al., 2020). Moreover, climate policy is a complex process where social and economic factors come together to create an optimal search beyond just reducing emissions and increasing the use of renewable energy. Therefore, due to its high dependence on temperature, precipitation, and climatic extremes, agricultural production and investments are affected by both physical climate risks and uncertainties in climate policies. Furthermore, agricultural investments usually require long-term planning, making investors' decision-making processes more difficult in an environment of uncertainty. Quantitative and temporal uncertainties in sustainable agricultural policies, adaptation investments and supply chains may cause farmers to postpone or abandon long-term investment decisions. Such effects are not only related to climate policy. There is empirical evidence that the physical impacts of climate change also affect the agricultural sector. Stevanović et al. (2016) stated that climate change will harm agricultural welfare globally, especially after 2050. The most basic predictions in this projection are that production will shift to higher latitudes and total yield loss will reach 0.3% per year. Ozdemir (2022), who investigates climate change's short- and long-term effects on agricultural productivity, confirms a long-term and negative relationship between agricultural productivity and climate change variables. Assunção (2016), Ortiz-Bobea et al. (2021), and Bai et al. (2024) also draw attention to findings predicting that the negative effects of climate change on agricultural productivity will continue increasingly. In contrast, Khalid et al. (2016) show that climate change affects countries' output performance, not agricultural value added.

So, what should be considered for the agricultural sector, which is severely affected by climate change, and for investments in this sector? How will increases in climate policy uncertainty affect investments in the agricultural sector? What kind of policy should be developed to prevent uncertainties hindering agricultural investments and encourage adaptation investments? The answers to these questions are important both academically and politically. Although they do not directly seek answers to such questions, some studies address climate policy uncertainty and agriculture from different perspectives. Among them, Wang et al. (2023) analyze the relationship between climate policy uncertainty and agricultural product prices through quantile connectivity and Johansen cointegration. Accordingly, high connectivity between climate policy uncertainty and agricultural product prices, especially in extreme quantiles, and also a long-term cointegration relationship are found. In another study, Wang et al. (2024) argue that climate policy uncertainty in China has a detrimental effect on green total factor productivity in agriculture. Li et al. (2024) investigate how green innovation in agricultural enterprises is affected by climate policy uncertainty. According to them, a positive relationship exists between climate policy uncertainty and green innovation in agricultural enterprises. In addition, government environmental subsidies and environmental concerns also contribute to this positive relationship. On the contrary, Aysan et al. (2024) argue that an unpredictable political environment reduces investors' confidence. The lack of political stability weakens the financial viability of long-term green technology investments, especially in developing economies. Therefore, it is possible to state that uncertainties in climate policies can hinder progress toward green economies through investor behavior. Borozan and Pirgaip (2025) also found similar findings in the USA. Accordingly, climate policy uncertainty significantly negatively affects renewable energy use, especially long-term. Renewable energy use, which is frequently emphasized as an important solution to mitigate the effects of climate change, faces difficulties due to uncertain climate policies. In another study on the USA, Noailly et al. (2022) provide evidence supporting the findings of the previous two studies. Investments in green technology and green bonds for a low-carbon economy are negatively affected by policy uncertainty.

Although the relationship between climate policy uncertainty and economic indicators has received increasing academic attention in recent years, studies on how this relationship is shaped in the agricultural sector are quite limited. The general tendency in the existing literature is limited to examining the negative effects of climate policy uncertainty on investment decisions while neglecting the agricultural sector, which is extremely sensitive to climate and increasingly important in economic terms. The agricultural sector is one of the sectors where long-term and capital-intensive investments have a significant share. It is also one of the sectors most vulnerable to climate change's physical and transition effects. In addition to being directly exposed to climate change, it has a structure that requires long-term and capital-intensive investments. However, the variability of climate policies and how uncertainties shape investment decisions in the sector have not been sufficiently examined. This study aims to fill this gap in the literature by analyzing the relationship between climate policy uncertainty and agricultural investments in an asymmetric framework. The analyses performed using the NARDL method and asymmetric causality test reveal how increases in uncertainty affect agricultural investments and whether this effect is asymmetric. Thus, it contributes to developing a more comprehensive understanding of the relationship between climate policy uncertainty and agricultural investments. In addition, the agricultural sector is also important for the United States. According to the 2023 data of the United States Department of Agriculture (USDA) Economic Research Service, the contribution of agriculture and other food-related industries to the US GDP is approximately $1.5 trillion. 5.5% of the US GDP is agricultural production, 10.4% of total employment is agricultural employment, and 12.9% of household expenditures is food. The highest share of USDA's expenditures on farm and food programs is allocated to nutrition assistance. According to USDA, 10.5% of greenhouse gas emissions in the USA in 2022 are caused by agricultural activities. These indicators clearly demonstrate the importance of the agricultural sector in the US economy and also its environmental impacts. While the agricultural sector significantly contributes to the country's economic growth and employment, it also has strategic importance due to its challenges in combating climate change. The economic impacts of climate change on the US agricultural sector and adaptation strategies support the main findings of this study, enabling a broader assessment of the relationship between climate policy uncertainty and agricultural investments. According to the USDA's (2013) comprehensive climate change and agriculture report, temperature increases, extreme weather events, depletion of water resources, and ecological imbalances caused by climate change threaten agricultural production and productivity, leading to economic instability. Extreme events, especially droughts, floods, and storms, increase production costs, trigger crop losses, and increase pressure on agricultural insurance systems. In this environment of economic uncertainty, the direction and sustainability of agricultural investments are also significantly affected. The adaptation strategies highlighted in the report offer various solutions for the agricultural sector to cope with these risks. However, the fact that national policy frameworks aimed at combating climate change are incompatible with the dynamics of local agricultural industries is one of the main factors limiting the effectiveness of the adaptation process. In contrast, the withdrawal of the US from the Paris Climate Agreement by the new president, Donald Trump (European Parliament, 2025), has further increased climate policy uncertainty. These uncertainties are expected to affect agricultural investments through various channels, such as increased risk perception, financing costs, adaptation investment disruption, and regional uncertainties. In such a case, establishing long-term and consistent climate policies for the US agricultural sector is critical for both the sustainability of investments and the increase of agricultural adaptation capacity. Therefore, the importance of the agricultural sector in the US and the increasing uncertainties in the fight against climate change reveals the importance of this study. The findings of this study can serve as a guide to understand better and manage the effects of climate policies on agricultural investments.

MATERIAL AND METHOD

This study examines the asymmetric relationships between climate policy uncertainty and agricultural investments in the USA from 1995 to 2022. Climate policy uncertainty (cpu) is an index developed by Gavriilidis (2021) that measures the effects of significant events related to climate policy, such as emissions news, renewable energy, global warming, and climate change. To create the climate policy uncertainty index, the terms "uncertainty, renewable energy, green energy, climate, etc." in 8 leading newspapers in the USA are scanned. In addition, this index can be used as a climate risk descriptor that reflects important volatility events related to climate policy (Ren et al., 2023). Agricultural investments (gfcf) represents the investments in the agricultural sector. Such investments are critical in increasing the agricultural sector's production capacity, ensuring its modernization, and improving efficiency. Agricultural investments not only mean providing production tools but also multifaceted contributions such as supporting rural development, increasing agricultural employment, and ensuring food security. Agricultural investments are the most fundamental part of agricultural production and are key to growth and development processes in agriculture (Butzer et al., 2012). Fixed capital investments include not only buildings, machinery, and equipment but also "cultivated assets yielding repeated products such as animals for breeding, dairy, draught, etc., or perennial tree, crop, and plant resources" (Vander Donckt and Chan, 2019). Such assets are of great importance in the sustainability of agriculture and long-term production planning, as they contribute to production cycles that span not only one season but also many years. Therefore, the gfcf indicator is theoretically and empirically influential in analyzing the agricultural sector's development process of capital accumulation and production capacity. The increase in these investments directly affects not only the quantity of agricultural outputs but also the quality of production and sectoral competitiveness (Butzer et al., 2012). The variable related to climate policy uncertainty is obtained from the https://www.policyuncertainty.com database. The variable related to agricultural investments is obtained from the Food and Agriculture Organization database (FAOSTAT). The descriptive statistics of these variables are given in Table 1.

Table 1. *Summary statistics*

	GFCF	CPU
Mean	29.82860	107.44400
Median	29.81661	93.13099
Maximum	40.78733	225.41320
Minimum	22.61642	57.56491
Std. Dev.	4.504570	51.25903
Skewness	0.497214	1.21183
Kurtosis	2.690901	3.26288
Jarque-Bera	1.265168	6.93374
Probability	0.531217	0.03122
Observations	28	28

According to Table 1, cpu has higher mean and median values than gfcf. Skewness values are positive, meaning the series is skewed to the right. Jarque-Bera test statistics show that the cpu series is not normally distributed. The study employs an annual dataset covering the period from 1995 to 2022, consisting of 28 observations, which is appropriate given the structure and scope of the model. The NARDL approach, which is well-suited for small sample sizes, is widely applied in the literature for low-frequency time series with limited observations.

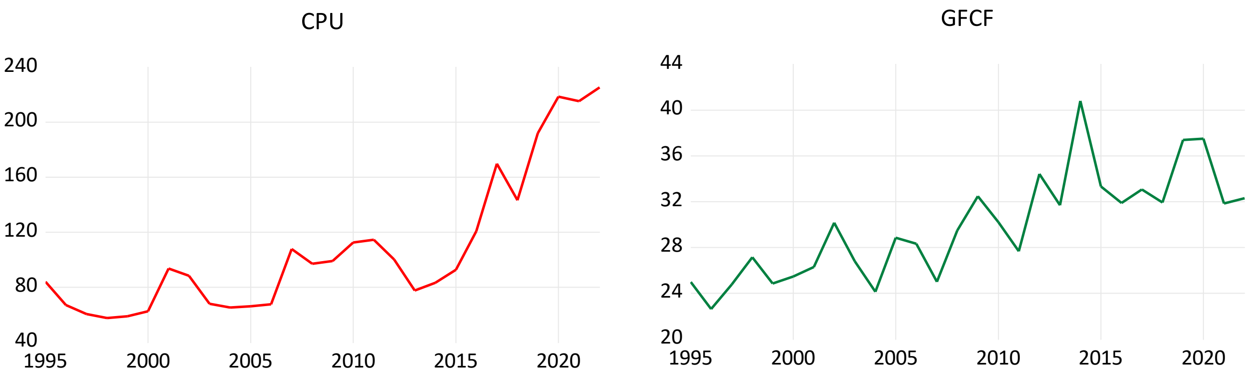

Figure 1. *Temporal dynamics of climate policy uncertainty and agricultural investment*

Source: www.policyuncertainty.com and FAOSTAT

Figure 1 shows the time series graphs of the variables. Although the cpu data fluctuates, it generally shows an increasing trend. Since the increases in the series indicate that uncertainties have increased, the discussions on the US's participation in the Kyoto Protocol in the early 2000s, the subsequent regulations of the Obama government limiting carbon emissions, the Paris Agreement in 2017, President Trump's rejection of new emission rules in 2020, and the acceleration of environmental policies, especially with the pandemic period, have also caused uncertainties to increase (Ren et al., 2023). The US's approach to global climate agreements, environmental regulations, and energy policies determines climate policy uncertainty. Events such as the Kyoto and Paris Agreements have caused these uncertainties to fluctuate (Gavriilidis, 2021). Similarly, gfcf also follows a fluctuating course. Low interest rates, agricultural subsidies, and the economic incentive packages implemented by the Obama administration after the Global Financial Crisis have increased investments. The increases experienced, especially after 2014, can be associated with increased investments in agricultural food security. The COVID-19 pandemic that followed increased the strategic importance of the agriculture and forestry sector, causing investments to reach record levels in 2020 (FAOSTAT Analytical Brief 54, 2021). Both series are included in the analysis by taking their natural logarithms.

In the study where the causality relationship between lgfcf and lcpu for the USA is examined, the stationarity levels of the variables are first determined through unit root tests. For this purpose, the stationarity levels, Augmented Dickey-Fuller (ADF) developed by Said and Dickey (1984), Phillips-Perron (PP) traditional unit root tests developed by Phillips and Perron (1988), and the single break unit root test based on the studies of Perron (1989) and Perron and Vogelsang (1992), are also used. Shin et al. (2014) use the NARDL model, allowing the effects of positive and negative shocks on the explanatory variables to be analyzed separately on the dependent variable, will be used. In order to analyze the asymmetric causality relationship, the variables are separated into positive and negative components and examined using the causality analysis developed by Hatemi-J (2012). When asymmetric causality tests and NARDL methods are used together, a more comprehensive analysis of the relationship between variables is achieved. While asymmetric causality tests the existence and direction of a relationship, the NARDL model explains how this relationship differs in the short and long term and whether it is asymmetric or not.

The Nonlinear Autoregressive Distributed Lag (NARDL) Model

The Autoregressive Distributed Lag (ARDL) model developed by Pesaran et al. (2001) has significantly contributed to the econometric literature. In the ARDL model, the dependent variable should be first-order stationary (I(1)), but the explanatory variables can be first-order stationary (I(1)) or stationary at level (I(0)). In this way, the ARDL model allows for analyzing the regression and cointegration relationships between the same and different-order stationary series. Shin et al. (2014) developed the NARDL model, which allows the analysis of the effects of positive and negative shocks on the explanatory variables on the dependent variable separately. This model allows for determining whether the effects of positive and negative shocks on the explanatory variables are the same as those on the dependent variable.

Based on the variables used in the analysis, an example asymmetric relationship can be presented with the following regression:

$$lgfcf_t = \beta^+ lcpu_t^+ + \beta^- lcpu_t^- + u_t \tag{1}$$

where β^+ and β^- are log-run coefficients of positive and negative changes in $lgfcf_t$, respectively. The positive and negative partial sums of the dependent variable are given in equation 2:

$$lcpu^+ = \sum_{i=1}^{t} \Delta lcpu_t^+ = \sum_{i=1}^{t} \max(\Delta lcpu_i, 0)$$
$$lcpu^- = \sum_{i=1}^{t} \Delta lcpu_t^- = \sum_{i=1}^{t} \min(\Delta lcpu_i, 0) \tag{2}$$

Based on equation 2, the NARDL model is presented as follows:

$$\Delta lgfcf_t = \alpha_0 + \alpha_1 lgfcf_{t-1} + \beta^+ lcpu_{t-1}^+ + \beta^- lcpu_{t-1}^- + \sum_{i=1}^{p} \gamma_i \Delta lgfcf_{t-i} + \sum_{i=1}^{q} \rho_i^+ lcpu_{t-i}^+ + \sum_{i=1}^{q} \rho_i^- lcpu_{t-i}^- \tag{3}$$

The model explained above is adapted according to the relationship detected by the asymmetric causality test.

Hatemi-J (2012) Asymmetric Causality Test

The basis of the asymmetric causality test developed by Hatemi-J (2012) is based on the symmetric causality test developed by Hacker and Hatemi-J (2006). The causality test uses the variables' positive and negative components (cumulative shocks). The basic idea underlying the development of this test is that the relationships between variables cannot always be symmetrical. Hatemi-J (2012), as in the study of Granger and Yoon (2002), separates the cumulative shocks of the variables and tests whether there is cointegration between the shocks using the cumulative shocks. According to Hatemi-J (2012), the variables $lcpu_t$ and $lgfcf_t$, whose causality relationship is investigated and assumed to be integrated, are defined in the random walk framework as shown below:

$$lcpu_t = lcpu_{t-1} + \epsilon_{1t} = lcpu_0 + \sum_{i=1}^{t} \epsilon_{1i} \tag{4}$$

and

$$lgfcf_t = lgfcf_{t-1} + \epsilon_{2t} = lgfcf_0 + \sum_{i=1}^{t} \epsilon_{2i} \tag{5}$$

In equations (4) and (5), $lcpu_0$ and $lgfcf_0$ are the initial values of the variables, and ϵ_{1i} and ϵ_{2i} are the sum of shocks that deviate the variables from the white noise. These shocks are defined as follows in Hatemi-J (2012):

$$\epsilon_{1i}^{+} = \max(\epsilon_{1i}, 0), \quad \epsilon_{2i}^{+} = \max(\epsilon_{2i}, 0) \rightarrow positive\ shocks\ of\ both\ variables$$

$$\epsilon_{1i}^{-} = \min(\epsilon_{1i}, 0), \quad \epsilon_{2i}^{-} = \min(\epsilon_{2i}, 0) \rightarrow negative\ shocks\ of\ both\ variables$$

and

$$\epsilon_{1i} = \epsilon_{1i}^{+} + \epsilon_{1i}^{-}, \quad \epsilon_{2i} = \epsilon_{2i}^{+} + \epsilon_{2i}^{-}$$

where, if we need to redefine the variables $lcpu_0$ and $lgfcf_0$ as follows:

$$lcpu_t = lcpu_{t-1} + \epsilon_{1t} = lcpu_0 + \sum_{i=1}^{t} \epsilon_{1i}^{+} + \sum_{i=1}^{t} \epsilon_{1i}^{-} \tag{6}$$

and

$$lgfcf_t = lgfcf_{t-1} + \epsilon_{2t} = lgfcf_0 + \sum_{i=1}^{t} \epsilon_{2i}^{+} + \sum_{i=1}^{t} \epsilon_{2i}^{-} \tag{7}$$

Finally, the cumulative shocks obtained here are expressed as new variables indicating the positive and negative shocks of the variables and are shown as follows:

$$lcpu_t^{+} = \sum_{i=1}^{t} \epsilon_{1i}^{+}, \quad lcpu_t^{-} = \sum_{i=1}^{t} \epsilon_{1i}^{-}, \quad lgfcf_t^{+} = \sum_{i=1}^{t} \epsilon_{2i}^{+}, \quad lgfcf_t^{-} = \sum_{i=1}^{t} \epsilon_{2i}^{-} \tag{8}$$

where $lcpu_t^{+}$ and $lcpu_t^{-}$ are cumulative positive and negative shocks of the current climate policy uncertainty variable, $lgfcf_t^{+}$and $lgfcf_t^{-}$are cumulative positive and negative shocks of agricultural investments, respectively. For example, positive/negative shocks of each variable will be determined using the VAR model:

$$\begin{bmatrix} lcpu_t^{+/-} \\ lgfcf_t^{+/-} \end{bmatrix} = \delta_0 + \delta_1 \begin{bmatrix} lcpu_{t-1}^{+/-} \\ lgfcf_{t-1}^{+/-} \end{bmatrix} + \cdots + \delta_{p+d_{max}} \begin{bmatrix} lcpu_{t-p+d_{max}}^{+/-} \\ lgfcf_{t-p+d_{max}}^{+/-} \end{bmatrix} + v_t \tag{9}$$

In equation (9), δ_0 represents the constant term vector, δ_1,…, $\delta_{p+d_{max}}$ represents the parameter vectors. v_t is the model's error term. The process after this stage is the same as the Hacker and Hatemi-J (2006) causality test, and causality analysis is performed on a model such as VAR (p). The following hypotheses are tested in the causality analysis:

$\mathbf{1^{st}}$ Null Hypothesis: There is no causality from positive climate policy uncertainty shock ($lcpu_t^{+}$) to positive agricultural investment shock ($lgfcf_t^{+}$)

$2nd$ Null Hypothesis: There is no causality from positive climate policy uncertainty shock ($lcpu_t^{+}$) to negative agricultural investment shock ($lgfcf_t^{-}$)

$\mathbf{3^{rd}}$ Null Hypothesis: There is no causality from negative climate policy uncertainty shock ($lcpu_t^{-}$) to positive agricultural investment shock ($lgfcf_t^{+}$)

$\mathbf{4^{th}}$ Null Hypothesis: There is no causality from negative climate policy uncertainty shock ($lcpu_t^{-}$) to negative agricultural investment shock ($lgfcf_t^{-}$)

$\mathbf{5^{th}}$ Null Hypothesis: There is no causality from positive agricultural investment shock ($lgfcf_t^{+}$) to positive climate policy uncertainty shock ($lcpu_t^{+}$)

$\mathbf{6^{th}}$ Null Hypothesis: There is no causality from positive agricultural investment shock ($lgfcf_t^+$) to negative climate policy uncertainty shock ($lcpu_t^-$)

$\mathbf{7^{th}}$ Null Hypothesis: There is no causality from negative agricultural investment shock ($lgfcf_t^-$) to positive climate policy uncertainty shock ($lcpu_t^+$)

$\mathbf{8^{th}}$ Null Hypothesis: There is no causality from negative agricultural investment shock ($lgfcf_t^-$) to negative climate policy uncertainty shock ($lcpu_t^-$)

Hypotheses are tested in a similar manner as in Hacker and Hatemi-j (2006). If these hypotheses are rejected, the sub-hypotheses show that there are causal relationships between the specified shocks.

FINDINGS

In the NARDL test, the stationarity level of the dependent variable is important. Therefore, first of all, the stationarity level of the variables should be determined through unit root tests. Table 2 shows the results of the ADF, PP, and Breakpoint Unit Root Tests.

Table 2. *Unit root test results*

Variables	ADF test		PP test		Unit root with break test		
	With Constant				*Intercept*		
	Test stat.	**Prob.**	**Test stat.**	**Prob.**	**Test stat.**	**Critical Value (5%)**	**Break date**
lcpu	-0.3097	0.9110	-0.3830	0.8987	-0.5574	-4.1936	2002
Δlcpu	-4.8633***	0.0006	-4.9072***	0.0006	-4.7765***	-4.1936	2014
lgfcf	-2.3741	0.1580	-2.2527	0.1936	-2.4483	-4.1936	2019
Δlgfcf	-6.2967***	0.0000	-13.6866***	0.0000	-4.6459**	-4.1936	2014
	With Constant and Trend				*Trend and Intercept*		
	Test stat.	**Prob.**	**Test stat.**	**Prob.**	**Test stat.**	**Critical Value (5%)**	**Break date**
lcpu	-2.7010	0.2439	-2.7010	0.2439	-3.1696	-4.6435	2018
Δlcpu	-4.8633***	0.0032	-5.0639***	0.0020	-4.2089**	-4.6435	2008
lgfcf	-4.8910***	0.0028	-4.8884***	0.0028	-4.5636	-4.6435	2017
Δlgfcf	-	-	-	-	-6.7489***	-4.6435	2015

***, **, and * indicates stationarity with a 1%, 5%, and 10% level of statistical significance, respectively. Δ is the difference operator.

According to the results of the unit root tests of the lcpu and lgfcf variables used in the study, both variables are not stationary at the level in the ADF and PP tests; however, when their first differences are taken, it is seen that they become stationary at the 1% level. According to the structural break unit root test, it is seen that both first differences are stationary. These findings show that the series are I(1) and that models with partial integration structures, such as NARDL can be used in the analyses. In order to apply the NARDL test and check the cointegration relationship between the variables, the F-Bounds test is applied to the created model. In addition, the Wald test is used to determine the short-term and long-term asymmetry. The test statistics results are given in Table 3.

Table 3. *Bounds Test Findings and Short- and Long-Term Asymmetry*

F-statistics	Significance Level	Critical Value	
		I(0)	I(1)
	10%	4.19	5.06
10.8256***	5%	4.87	5.85
	1%	6.34	7.52
Short-term asymmetry		***Long-term asymmetry***	
3.37739** (0.0392)		6.70227** (0.0214)	

***, **, and * indicates stationarity with a 1%, 5%, and 10% level of statistical significance, respectively. For the cointegration test, H_0: There is no cointegration.
Wall test is used to test the existence of short-term and long-term asymmetry.

The null hypothesis (H_0) of the F-statistic obtained from the NARDL bounds test is that there is no cointegration between the series. Therefore, the null hypothesis must be rejected in order for cointegration to occur between the series. If the Value of the F-statistic is greater than the upper limit value, the null hypothesis is rejected at that significance level; in other words, it is decided that there is a long-term relationship between the series. As can be seen from the table, the Value of the F-statistic (10.8256) is greater than the upper limit value of the 1% significance level (7.52). Therefore, the H_0 hypothesis is rejected; in other words, it is concluded that there is a long-term relationship between the series. Additionally, according to the Wald test findings, cpu affects gfcf asymmetrically in the short- and long-term. As a result, long-term coefficients can be used to examine the degree and direction of the effect of the variables. The NARDL short-term and long-term findings created from this are given in Table 4.

Table 4. *NARDL (1,3,3) model results*

Short-run coefficients
Dependent variable $\Delta lgfcf$

Variable	Coefficient	t-Statistic	Prob.
C	3.416869***	6.087596	0.0000
@TREND	0.117787***	5.974763	0.0000
$lcpu^{+}$	-0.076978	-0.589758	0.5655
$lcpu^{+}$(-1)	0.418944***	3.207091	0.0069
$\Delta lcpu^{+}$(-1)	0.378799**	2.625731	0.0210
$lcpu^{-}$	0.521200**	2.169257	0.0492
$lcpu^{-}$(-1)	-0.973536***	-4193921	0.0011
$\Delta lcpu^{-}$(-1)	-0.978922***	-3.354266	0.0052
ECT (-1)	-0.974111***	-6.121554	0.0000
Long-run coefficients	**Coefficient**	**t-Statistic**	**Prob.**
$lcpu^{+}$	-0.386959**	-2.259646	0.0417
$lcpu^{-}$	1.091052*	2.012377	0.0654
Diagnostic tests	**Test statistic**	**Prob.**	
Jarque-Bera Normality test	0.627451	0.7307	
Serial correlation LM test	0.771642	0.4857	
Breusch-Pagan-Godfrey heteroscedasticity test	0.901536	0.5572	
CUSUM and CUSUMSQ		Stable	

***, **, and * indicates stationarity with a 1%, 5%, and 10% level of statistical significance, respectively.

Table 4 presents the estimation results of the NARDL (1,3,3) model, where the numbers in parentheses indicate the selected lag structure: one lag for the dependent variable and three lags each for the positive and negative partial sums of the independent variable. The optimal lag length of the NARDL model has selected based on the Akaike Information Criterion (AIC). Accordingly, the NARDL(1,3,3) structure has preferred, incorporating one lag of the dependent variable and three lags of the decomposed positive and negative components of the independent variable. This lag structure balances model complexity with explanatory power and passes all stability and diagnostic tests. Firstly, the model has a normal distribution and does not contain autocorrelation and heteroscedasticity problems. According to the short-term coefficient in Table 4, it can be said that positive shocks do not have a significant effect on agricultural investments, but negative shocks affect agricultural investments positively. However, ECT is negative and its absolute value is very close to 1. So, short-term shocks that occur quickly return to the long-term equilibrium. According to the long-term coefficients, a positive shock (increase in uncertainty) in climate policy uncertainty decreases agricultural investments by 0.39% ($p<0.05$). Planning to reduce climate policy uncertainties is essential to increasing investments in the sector. Fixed capital investments in the economy are one of the essential components of growth. In particular, this contraction in the agricultural sector can slow down real growth along with sectoral stagnation. For this reason, increasing agricultural investments is necessary to increase agricultural production and income.

The NARDL test shows long- and short-term effects but does not tell whether there is causality between variables. Asymmetric Granger causality tests, on the other hand, provide a more accurate analysis by testing the separate effects of positive and negative shocks.

The Hatemi-J (2012) causality test, which also considers asymmetric relationships, is conducted, and its results are given in Table 5.

Table 5. *Hatemi-J (2012) asymmetric causality test results*

H_0 hypothesis	MWALD	Critical Value
$lcpu^{+} \nrightarrow lgfcf^{+}$	5.809	6.108
$lcpu^{-} \nrightarrow lgfcf^{-}$	3.613	6.577
$lcpu^{-} \nrightarrow lgfcf^{+}$	1.247	19.959
$lcpu^{+} \nrightarrow lgfcf^{-}$	91.218**	17.522
$lgfcf^{+} \nrightarrow lcpu^{+}$	0.089	6.136
$lgfcf^{-} \nrightarrow lcpu^{-}$	0.0278	6.004
$lgfcf^{-} \nrightarrow lcpu^{+}$	0.217	20.931
$lgfcf^{+} \nrightarrow lcpu^{-}$	5.947	21.048

** indicates a causality correlation with a 5% level of statistical significance.

When the results in Table 5 are examined, it is seen that there is a significant asymmetric causality relationship from lcpu positive shocks to lgfcf negative shocks at the 5% significance level. Positive shocks in climate policy uncertainty can be sudden changes in environmental policies, decreased predictability for the future, tightening of international climate regulations, or increased political uncertainties. Increased uncertainty shows that agricultural investments are negatively affected. Unpredictable changes in environmental regulations can increase investment costs. This situation can affect sectors sensitive to regulations, especially agriculture and forestry. In addition, when the analysis results are examined, it is seen that the causality relationship does not work in reverse. While increases in climate policy uncertainty have direct negative effects on lgfcf, decreases in uncertainty do not have the same positive effect on lgfcf. This shows that investors' sensitivity in periods of uncertainty is more substantial than their optimism in periods of predictability.

The findings of this study are broadly consistent with previous literature that confirms the negative relationship between climate change and agricultural productivity (Assunção, 2016; Ortiz-Bobea et al., 2021; Ozdemir, 2022; Bai et al., 2024), yet they diverge significantly by presenting asymmetric responses specific to the agricultural sector. Studies such as Ren et al. (2022), Zhang et al. (2023), Abdulai et al. (2024), and Zhao et al. (2025) have empirically demonstrated that overall investment levels decline as uncertainty increases. However, they have not thoroughly examined how this effect varies across sectors. Fuss et al. (2008) and Feyen et al. (2020) emphasize that climate policy uncertainty negatively impacts investments, particularly in energy and carbon-intensive sectors. In contrast, this study highlights asymmetric responses specific to agricultural investments. The findings reveal that while agricultural investments decline rapidly in response to increasing uncertainty, they do not recover at the same pace when uncertainty decreases. Moreover, reducing agricultural investment levels due to climate policy uncertainty also disrupts adaptation and sustainability-related investments. This outcome aligns with the findings of Noailly et al. (2022), Aysal et al. (2024), and Borozan and Pirgaip (2025), who suggest that uncertainty diminishes investor confidence.

It is beneficial to discuss what the findings of this study mean for the USA. USDA's programs promote sustainable agricultural practices, support mechanisms for climate change adaptation, and carbon credit systems, among the key factors shaping agricultural investments. However, climate policy uncertainties may limit these support mechanisms' capacity to encourage long-term investment decisions. The USA should adopt long-term and predictable policies to encourage agricultural investment and reduce climate policy uncertainty. First, Trump's mistake of withdrawing from the Paris Climate Agreement should be reversed, and a more transparent and decisive climate policy framework should be created that aligns with the agreement's commitments. Second, low-interest loans, subsidies, and tax incentives can be provided to support agricultural adaptation investments. In addition, incentives can be implemented to ensure farmers earn from carbon reduction efforts. Effective policies can remove barriers to agricultural investment, making the sector more resilient to the impacts of climate change and aligned with environmental sustainability goals. These policies are vital not only for economic growth but also for global human and environmental development.

CONCLUSION

This study investigates the asymmetric relationship between climate policy uncertainty and agricultural investments in the United States from 1995-2022. The asymmetric causality test provides additional evidence for the asymmetric relationships identified by the NARDL model. Therefore, the most significant asymmetric finding of the study indicates that as climate policy uncertainty increases, agricultural investments decline. This can be explained by the differentiation of agricultural investors' risk perceptions and investment decision-making processes in response to uncertainty. While investments rapidly decrease when uncertainty rises, it has been observed that a decrease in uncertainty does not lead to an equally rapid increase in investments. This situation can be associated with factors such as the long return period of agricultural investments, investors' risk aversion tendencies, and the inconsistency of climate policies weakening the confidence environment. NARDL also provides a distinction between short- and long-term effects. Shocks occurring in the short term can be neglected as they quickly return to the long-term equilibrium. However, in the long term, climate policy uncertainty has a discouraging effect on agricultural investments. Climate change affects many areas in the agricultural sector, from production to employment, food security to natural resource management, and climate policy uncertainty deepens this relationship. Therefore, while climate change already causes physical and economic damage to the agricultural sector, climate policy uncertainty creates a double threat by preventing long-term investments that will reduce these damages. The decrease in agricultural investment can have undesirable economic and environmental consequences. The most obvious effect is the decrease in agricultural production. The most devastating result of this, assuming a continuing increase in population, is famine. The decrease in agricultural production can also affect agricultural employment and economic growth. Decreased agricultural production can reduce the food supply and increase prices. Moreover, inadequate agricultural investments in climate adaptation may negatively impact the ecosystem in the long term by increasing vulnerability to the impacts of climate change.

The relationship between climate policy uncertainty and agricultural investments analyzed in this study is specific to the United States; however, it does not examine how similar dynamics operate in different countries or regions. While the findings suggest that the implications may not be promising for the rest of the world, it is also evident that more evidence is needed. Additionally, although the NARDL model effectively captures asymmetric effects, it may be complemented by different methods to assess structural regime changes fully. Future studies could conduct in-depth analyses using alternative methodologies. Furthermore, they can be expanded to a sectoral perspective to understand the effects of climate policy uncertainty on investments in other countries. In addition, how uncertainty perception is formed at the level of farmers and agricultural enterprises and how it affects decision-making processes can be examined in more detail.

Contribution Rate of Researchers Declaration Summary

The authors declare that they have contributed equally to the article and have not plagiarized.

Conflict of Interest Declaration

The authors of the article declare that there is no conflict of interest between them.

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