The determinants of forest area in Brazil: Ethanol production, exports of crops and livestock, and asymmetric impact of temperature change

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Abstract: This paper evaluates the long-run impact of fuel ethanol production, exports of crops and livestock, and the asymmetric impact of temperature change on the forest area in Brazil. We use the non-linear autoregressive distributed lag model and annual data between 1990 and 2022. An increase in ethanol production or in exports of crops and livestock importantly reduces the forest area in Brazil, in the long-run. We demonstrate that while positive temperature change does reduce forest area in the long-run, falling temperatures do not guarantee the regeneration of lost forests. A temperature change increase of 1°C leads in the long term to a significant and very worrying reduction in the forest area of Brazil, of almost 9.8%. Some policy recommendations are drawn: *i)* To reduce GHG emissions, Brazil should encourage R&D and innovation in energy efficiency and renewable energy (e.g., solar, wave), especially in second-generation or third-generation biofuels production, through appropriate competitive credits and subsidies; *ii)* Brazil should encourage agricultural research to increase agricultural yields and the use of aeroponics for vegetable culture or smart agriculture, because this will lead to less pressure on agricultural lands and therefore on deforestation; *iii)* A strategy to preserve or even to recover the Brazilian Amazon forest should be established combined with a strategy for developing green tourism.

Keywords: Forest area; Temperature change; Ethanol production; Exports of crops and livestock; Non-linear autoregressive distributed lag; Brazil.

Jel classifications: C22; F18; O13 ; O54 ; Q15 ; Q23 ; Q54.

1. Introduction

Agriculture, which removes trees for crops and pasture to meet the demand for food, animal feed, biofuels, and lumber, is the primary driver of deforestation. Deforestation has serious negative effects on the ecosystem, including reduced soil quality, a decline in biodiversity, and greenhouse gas (GHG) emissions that fuel climate change. Important agricultural practices that contribute to this detrimental effect include the development of monoculture crops like soy and palm oil, the manufacture of lumber, and large-scale livestock ranching.

About 70% of the World's tropical forests are found in the Brazilian Amazon, which is vital to the country's economy by protecting biodiversity, sustaining the livelihoods of local communities and Indigenous peoples, and offering vital ecosystem services like soil stabilization, flood mitigation, and climate and water regulation (Kauano et *al.*, 2020). Brazil's forest area has continuously decreased from 5888980 km^2 in 1990 to 4941960 km^2 in 2022. During the same period, there are increases in temperature change from 0.446°C to 1.03°C, fuel ethanol production from 6.6 million metric tons of oil equivalent (MMTOE) to 15.5, and exports of crops and livestock from 14 billion US$ constant 2015 to 112 (World Bank, 2025; Food and Agriculture Organisation, 2025).

Kröger (2017) emphasizes that non-forest economic and political areas should be taken into account when analyzing forest policies. In 2012, the Brazilian Congress enacted a New Forest Code that significantly loosened the 1965 Code. The law-changing initiative served as an example of the conflict between the new sustainability expectations of various "green economy" proponents and the powerful landholders' lobby. He explains how, since 2012, the concept of sustainability with respect to forests and other land uses has evolved. He believes that Brazil offers a crucial case study for examining how certain aspects of the "brown economy" and "green capitalism" paths actually complement one another, and how the forest sector has emerged as a major player in this alliance at the expense of "socio-environmentalism". Costa et *al.* (2025) emphasize several important lessons for decision-makers who want to reduce deforestation and recall that foreign deforestation activity is significantly impacted by domestic forest regulations due to the interconnectedness of international markets through commerce. These initiatives should prioritize both local and international policy coordination, take into account the market incentives and responses of private enterprises, combine environmental regulations with poverty reduction programs, and take into consideration political restrictions and frictions.

It is undeniable that increased temperatures and climate change negatively impact forests, and deforestation exacerbates climate change. Between 2010 and 2018, Gatti et *al.* (2021) measured the lower-tropospheric concentrations of carbon dioxide and carbon monoxide at four locations in Amazonia using 590 aircraft vertical profiles. They discover that, mostly due to regional variations in carbon-monoxide-derived fire emissions, total carbon emissions are higher in eastern Amazonia than in the western region. In particular, southeastern Amazonia is a net carbon emitter. They investigate how climate change and deforestation trends affect carbon emissions at their study sites and discover that in the eastern Amazon, increased deforestation and the lengthening of the dry season appear to increase ecosystem stress, fire frequency, and carbon emissions. This is consistent with previous research showing that climate changes throughout Amazonia are causing an increase in tree mortality and a decrease in photosynthesis.

ARGUS (2025) states that deforestation in Brazil's Amazon rainforest grew modestly over the past year, driven mostly by increased forest fires rather than clear-cutting. The evolving profile of deforestation emphasizes obstacles for Brazil to fulfill its 2030 aim of eradicating all deforestation, especially since the delicate ecology has seen less rain. Almost every one of the 459 municipalities in Brazil's Amazon basin saw some degree of dryness last year. Deforestation increased by 4% from 4321 km^2 to 4495 km^2 during the 12 months ending in July. Although 85% of the deforestation was still driven by clear-cutting, 15% of the loss was due to climate-related degradation. It was almost twice as high as the previous record of 8% in 2016 and the highest level of degradation-related losses ever recorded. It forecasts that deforestation in the Brazilian Amazon would have decreased by 8% over that time if climate-related degradation had not increased. Tropical woods are now more susceptible to fires due to climate change. The Amazon basin's annual rainy season has seen a 2.1 cm decrease in rainfall due to deforestation, which has exacerbated the dry season and raised the risk of forest fires. The Brazilian Amazon has lost around 550000 km2, or about 14% of its total original vegetation, since 1985. While the Amazon biome saw a rise in deforestation, other areas saw significant decreases. Franco et al. (2025) use parametric statistical models to examine long-term atmospheric and land cover change by using data about 29 regions of the Brazilian Legal Amazon, ranging from 1985 to 2020. Deforestation has considerably raised surface air temperatures and decreased precipitation during the Amazonian dry season, but worldwide emissions are the main cause of the increase in atmospheric methane (CH4) and carbon dioxide (CO_2) mixing ratios. Approximately 74% of the 21 mm dry season drop and 16.5% of the 2°C increase in maximum surface air temperature over the previous 35 years can be attributed to deforestation.

Fuel ethanol production is nowadays an important economic sector in Brazil. Although the vast majority of the indigenous inhabitants of Brazil were wiped off, Cortez (2023) notes that over 60% of the natural forest is still intact. Nearly 200 million hectares (Mha), or nearly 23% of Brazil's total area, are made up of large pastureland, which is the primary cause of deforestation that threatens the Brazilian Amazon forest, which makes up nearly 50% of the country. He believes that corn ethanol can help Brazil maintain the Brazilian Amazon Forest and greatly enhance its land use and sustainability metrics. To achieve these objectives, Brazil needs to put anticyclical policies into place in order to build a new national development model and include the current stakeholders in this difficult process. According to Aguiar et al. (2025), Brazil has established a spectacular ethanol fuel sector since the first biofuel policy (Proalcool) was introduced in 1975. This business is now a significant part of the nation's plan to reduce GHG emissions. They discovered that the transportation industry was able to reduce emissions significantly by using ethanol fuel, which resulted in GHG emission reductions of 39–46% when compared to gasoline and a total averted emission of more than 828 million metric tons of carbon dioxide equivalent. They note that while market forces have played a more significant role in the growth of the ethanol industry, biofuel regulations also have a significant impact. Because the new biofuel policy (RenovaBio) overlooks emissions from land use change (LUC), there are worries about how it may affect the environment. They advise biofuel strategies to take into account the possible negative effects of LUC and to take decisive actions to stop deforestation in order to prevent negative consequences.

Sousa and Ribeiro (2025) point out that Brazil has emerged as a global leader in agricultural exports, exporting important commodities to foreign markets, especially China, the European Union, and the United States, including soybeans, cattle, corn, and sugarcane. Economic growth, trade surpluses, and rural employment have all benefited greatly from this export-driven agricultural boom, but it has also prompted grave concerns about social injustice, environmental sustainability, and domestic food security. Deforestation, the displacement of small-scale farmers, higher food prices, and less availability of basic foods for low-income communities are all results of the shift toward large-scale agribusiness and monoculture farming. The Brazilian government has responded to these issues by implementing some policy measures, such as land-use controls, food price stability programs, and social assistance programs like the National School Feeding Program and Bolsa Família. However, because agricultural interests continue to dominate governmental decisions, the effectiveness of these initiatives is still uneven. Govoni et al. (2025) highlight that Brazil, a major exporter of animal feed proteins, was severely impacted by China's shift toward increased consumption of animal proteins, which significantly altered global agricultural dynamics. According to their estimates, 10% of China's total protein and 24–29% of its animal protein come from Brazil. In 2020, China virtually imported 17.8 million hectares of Brazilian land due to its dependency on Brazilian soybeans for livestock feed. Despite a decline in direct deforestation associated with soybean production, indirect deforestation continues as soybean farming continues to grow, frequently displacing other land uses.

Pereira and Bernasconi (2025) present their analysis of the Brazilian beef based on 2021, 2022, and 2023 data. Brazil is the biggest exporter of beef and the second-largest producer in the world. With 8.4% of the gross domestic product (GDP) and over 8.9 million jobs in 2024, Brazil's beef industry is a significant contributor to the nation's economy. Over the past ten years, the percentage of Brazilian beef exported has increased, even though around 70% of it is consumed domestically. China, which accounted for 59% of Brazilian beef exports in 2023, is also the export market most exposed to deforestation, having grown from 124000 hectares in 2015 to 564000 hectares in 2023. Brazil's deforestation for cattle ranching has significantly shifted toward the Amazon since 2017 (62% of the country's total in 2023 compared to 40% in 2017). This implies that concentrating efforts on hotspots could considerably lower conversion and deforestation while having a negligible effect on the production of cattle. Satellite monitoring data show that deforestation decreased by 26% in the Cerrado and 31% in the Amazon in 2024, due to measures to control deforestation taken by the federal government since 2023.

In this study, we will evaluate the long-run impact of fuel ethanol production (EP) and exports of crops and livestock (ECL) on Brazilian forest area (FA) by using time series annual data between 1990 and 2022. Also, by using the non-linear autoregressive distributed lag (NARDL) approach, the asymmetric impact of temperature change (TC) on deforestation is evaluated. Our research could be of great interest because, to the best of our knowledge, there is: *i)* No econometric study about the impact of temperature change (or climatic change) on forest area, whether in Brazil or in other countries. The existing studies are about scenario analysis; *ii)* Absence of econometric time series analysis about the impact of exports of crops and livestock on deforestation, whether for the Brazil case or another country; *iii)* No time series or even panel econometric studies about the impact of energy consumption on forest area in Brazil. The structure of our study is the following. Literature review (Section 2), data and stationary tests (Section 3), cointegration and long-run estimates (Section 4), results discussion (Section 5), and conclusions with recommendations (Section 6).

2. Literature review

Deforestation is influenced by several factors. One of the most studied in the literature is gross domestic product (GDP). The impact of GDP per capita (GDPC) on forest area varies with the considered countries or panel of countries, or even regions in the same country. This relationship could be linear and positive (Tan and Tachibana, 2025), U-shaped (Pablo-Romero et *al.*, 2023), inverted U-shaped (Halkos and Skouloudis, 2020; Tan and Tachibana, 2025), N-shaped (Benedek and Fertő, 2020), or even inverted N-shaped (Bhattarai and Hammig, 2001). For Brazil, some research indicates that economic growth expands deforestation (Faria and Almeida, 2016), while others conclude that economic growth can be realised with a reduction in deforestation (Souza and Barbosa, 2025).

In our study, we focus on the impact of temperature change, exports of crops and livestock, and fuel ethanol production. The absence of an econometric study about the impact of temperature (or climatic) change is noticeable. According to Lapola *et al.* (2011), there are many different climate change scenarios for the Amazon region. An extreme scenario predicts a catastrophic increase in temperature of 3.8°C and a 30% loss in precipitation by 2050. Their findings, which are based on a spatially explicit modeling framework for the Brazilian Amazon by 2050, demonstrate that, in the absence of adaptation, climate change may have a significant effect on the yields of crops that are frequently grown in the Amazon (for example, in the worst-case scenario, soybean yields are reduced by 44%). In comparison to a scenario of mild climate change, a severe regional climate change would result in an increase of deforestation by 20% (181000 km^2) in the Amazon and by 273% (240000 km^2) in the Cerrado. Either a 26%–40% decrease in livestock output until 2050 or a doubling of the average cattle density from 0.74 to 1.46 head per hectare will be necessary to stop deforestation in the Brazilian Amazon forest by 2020, and the Cerrado by 2025. These findings imply that the reduction of yields implies further deforestation. Also, in scenarios that examine low levels of exceedance and overshoot beyond 1.5 °C, Munday et al. (2025) assess the hazards of irreversible consequences on forest ecosystems, such as Amazon forest loss and high-latitude woody encroachment. They recommend that lowering global temperatures below 1.5°C helps to reduce long-term forest loss.

Other studies have also taken into account how agricultural activity affects forest acreage. According to the majority of this research (Angelsen, 2010; Pablo-Romero et *al.*, 2023; Pratzer *et al.*, 2023), the effects of agricultural activities are negligible or even advantageous where Indigenous land management is prevalent (Pratzer *et al.*, 2023). While Sousa *et al.* (2022) demonstrate that cow farming reduces deforestation, panel studies concerning certain Brazilian towns or regions indicate that soybean and cattle production may promote deforestation (Carvalho and Domingues, 2016; Faria and Almeida, 2016).

Silva *et al.* (2023) use data for soybean-producing municipalities in the Brazilian state of Mato Grosso from 2004 to 2017 with an empirical spatial modeling approach. The findings indicate that municipalities with higher and more consistent soybean production that was not intended for international markets during the study period were more strongly linked to deforestation, even though the majority of the soybeans produced in Mato Grosso during that time (60%) were intended for international markets. Additionally, there was a substantial correlation between soybean production and the expansion of pasture and livestock in these municipalities. Carreira et *al.* (2024) use remote-sensing data about Brazilian municipalities between 2000 and 2017 and show that more exposure to new genetically engineered soy seeds leads to faster deforestation due to cropland expansion. The impacts of the new soy technology on deforestation are lessened by trade with China, but there is no discernible link between local exposure to Chinese demand and deforestation. According to their findings, deforestation in Brazil was more significantly influenced by productivity advances engendered by municipal competition than by Chinese demand alone.

Few papers consider the impact of energy production or consumption on forest area to conclude that the impact is negative (Pablo-Romero *et al.*, 2023) or is insignificant (Aydin *et al*., 2024). Anwar *et al.* (2021) consider 33 partner economies of the Belt and Road Initiative (BRI) and annual data between 1986 and 2018. They find feedback Granger causality between the forest area and renewable energy consumption. Raihan *et al.* (2022) consider Malaysia and annual data from 1990 to 2019. They show the existence of bidirectional Granger causality between energy use and deforestation, and a unidirectional causality from agricultural land growth to energy use, and deforestation to agricultural land growth. Pablo-Romero *et al.* (2023) study on 19 Latin American and Caribbean countries shows that Energy consumption per capita reduces forest area per capita. Aydin *et al.* (2024) use data about Finland covering the years 1970 to 2018 to confirm the inverted U-shaped EKC hypothesis between per capita GDP and forest footprint (FF). Biomass energy consumption has a non-significant impact on FF. Raihan and Tuspekova (2022) use annual data about Brazil spanning the period 1990-2019, the autoregressive distributed lag (ARDL) and the dynamic ordinary least squares (DOLS) approaches. They conclude that agricultural output increases carbon emissions, while renewable energy consumption and forest areas reduce them.

Our literature review shows that there is no econometric study about the impact of fuel ethanol production and temperature change on forest area or deforestation in Brazil. Also, there is no econometric time series analysis about the impact of exports of crops and livestock on forest area in Brazil, and even in other countries.

3. Data and stationary tests

Our study uses annual data about Brazil and covers the period 1990 to 2022. We use the following variables: *a)* Forest area (FA) in km^2; *b)* Temperature change (TC) on land in Celsius degrees (°C). It is the mean surface temperature change in a considered year with respect to a baseline climatology, related to the period 1951–1980; *c)* Exports of crops and livestock (ECL) products in 1000 US$. They are divided by the GDP deflator for the USA base year 2015, then multiplied by 100 to get their value in 1000 US$ constant 2015; *d)* Fuel ethanol production (EP) in million metric tons of oil equivalent (MMTOE). Forest area and the US GDP deflator data are obtained from the World Bank (2025), exports of livestock and temperature change data are obtained from the Food and Agriculture Organisation (FAO, 2025), and data concerning ethanol production are taken from the US Energy Information Administration (EIA, 2025). The natural logarithmic transformation is applied to our variables, except the temperature change variable, before econometric computations.

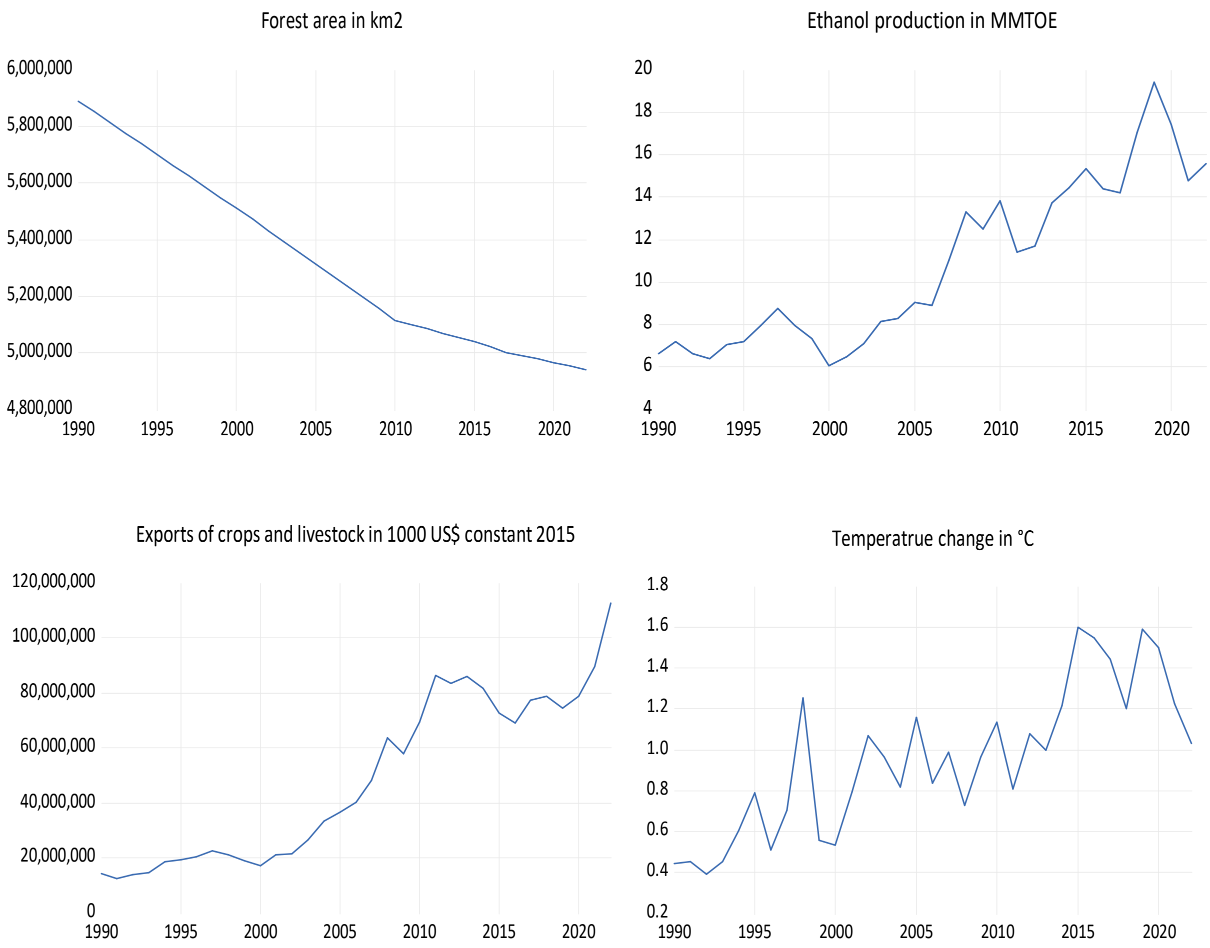

Fig. 1. Plots of variables

The plots of our considered variables are given in Fig. 1, and Table 1 gives some descriptive statistics. The forest area has steadily diminished from 5888980 km² in 1990 to 4941960 km² in 2022, signifying a decrease of 16% during this period. We can see that the graph of forest area has registered a net decrease in its absolute value slope in 2010 and in 2017. Ethanol production has a net upward tendency, passing from 6.6 MMTOE in 1990 to 15.6 MMTOE in 2022, meaning an increase of 136% between 1990 and 2022. A minimum value of 6 MMTOE was registered in 2000, and a maximum value of 19.4 in 2019 during the COVID lockdown. Exports of crops and livestock have also experienced a noticeable net upward trend during the considered period, passing from 14 billion US$ constant 2015 in 1990 to 112 billion in 2022, meaning a significant increase of 700%. Temperature change has net fluctuations but a net upward tendency with a value of 0.446 °C in 1990 and 1.03 °C in 2022, signifying that temperature change has more than doubled during this relatively short period. The minimum temperature change of 0.39 °C was realized in 1992, and the maximum change of 1.6 °C was realized in 2015. Our calculations show a negative and high correlation of forest area with EP (-0.89), ECL (-0.93), and TC (-0.81). This pushes our curiosity to know more about these correlations and to estimate long-run coefficients or elasticities.

Table 1. Descriptive statistics

	FA	EP	ECL	TC
Mean	5328353	10.82020	48517259	0.950879
Median	5273839	9.032358	40018207	0.966000
Maximum	5888980	19.39079	1.12E+08	1.601000
Minimum	4941960	6.038069	12518540	0.391000
Std. Dev.	306863.8	3.883900	30176891	0.356075
Skewness	0.366722	0.460002	0.294816	0.194046
Kurtosis	1.740541	1.931117	1.637823	2.092292
Jarque-Bera	2.920745	2.734764	3.029388	1.340006
Probability	0.232150	0.254773	0.219875	0.511707
Sum	1.76E+08	357.0666	1.60E+09	31.37900
Sum Sq. Dev.	3.01E+12	482.7097	2.91E+16	4.057266
Observations	33	33	33	33

We start our econometric calculations by assessing our series's stationary characteristics. An expansion of traditional unit root tests, such as the Augmented Dickey and Fuller (ADF, 1979) test, the Zivot and Andrews (1992) test allows for the existence of a structural break at an unknown point. If the data exhibit a structural break, traditional unit root tests may erroneously fail to reject the unit root null hypothesis, misinterpreting a one-time level or trend shift as evidence of non-stationarity. Rather than assuming the most likely break date beforehand, Zivot and Andrews (1992) decide it endogenously. The alternative hypothesis asserts that the series is trend-stationary with a single structural break, while the null hypothesis claims that the series has a unit root without any structural breaks. By taking into account any breaks, this test improves the reliability of stationarity testing in financial and macroeconomic time series that may have experienced economic crises, policy changes, or regime changes. From Table 2, we deduce that ethanol production and temperature change variables are stationary at the level, i.e., are I(0), whereas forest area and exports of crops and livestock are stationary after the first difference, i.e., are I(1).

Table 2. Zivot-Andrews tests of stationarity

Variables	ecl	ep	fa	tc
L-ZA	-3.50	-4.72[c]	-1.10	-4.75[c]
L-Break point	2007	2007	2017	2014
FD-ZA	-5.53[a]	-5.44[a]	-10.82[a]	-5.44[a]
FD-Break point	2012	2001	2011	2012
Order of Integration	I(1)	I(0)	I(1)	I(0)

L-ZA is the Zivot and Andrews (1992) test statistic at the level, and FD-ZA is the Zivot and Andrews (1992) test statistic after first-difference. L-Break point and FD-Break point denote break points at the level and after the first difference, respectively. Statistical significance levels at 1% and 10% are denoted by superscripts [a] and [c], respectively. This test is computed with an intercept and a maximum lag length of 4. Critical values -5.34, -4.93, and -4.58 are for the 1%, 5%, and 10% significance, respectively.

4. NARDL cointegration and long-run estimates

In this study, we will try to evaluate the impact of ethanol production, exports of crops and livestock, and temperature change on forest area. Following the literature that expresses forest area or deforestation as a function of some variables as GDP, trade openness, biomass consumption, and percentage of rural population (Faria and Almeida, 2016; Ajanaku and Collins, 2021), we estimate forest area in Brazil as a function of ethanol production, exports of crops and livestock, and temperature change[1]. In particular, we will estimate the asymmetric impact of temperature change on forest area by evaluating the impact of increases and decreases in temperature change separately. Thus, we estimate the following model:

$$fa_t = c_1 + \alpha_1 ep_t + \alpha_2 ecl_t + \alpha_3 tc_t^+ + \alpha_4 tc_t^- + \varepsilon_{1t} \tag{1}$$

Where tc_t^+ and tc_t^- are partial sums of increases and decreases in tc_t, respectively, and are calculated as follows:

$$tc_t^+ = \sum_{i=1}^{t} \Delta tc_i^+ = \sum_{i=1}^{t} max(\Delta tc_i, 0) \quad , \quad tc_t^- = \sum_{i=1}^{t} \Delta tc_i^- = \sum_{i=1}^{t} \min(\Delta tc_i, 0) \tag{2}$$

[1] The estimate of a symmetric ARDL model did not gave us significant results.

Since we evaluate the asymmetric impact of temperature change on forest area, the use of a non-linear model such as the NARDL model developed by Shin *et al.* (2014) is appropriate. This NARDL approach is an extension of the ARDL methodology developed by Pesaran and Pesaran (1997), Pesaran and Smith (1998), and Pesaran *et al.* (2001). Non-linear ARDL models are capable of detecting ''hidden cointegration'' and asymmetric effects both in the long- and short-run when linear models, such as ARDL ones, are not able. Also, NARDL models have the advantages of ARDL models as variables can be mixed, integrated I (0) or I (1), avoid endogeneity problems, and can provide good estimates even with small samples.

The NARDL representation of model (1), considering the restricted trend case, is:

$$\begin{aligned}\Delta fa_t &= c_2 + \alpha t + \beta_0 fa_{t-1} + \beta_1 ep_{t-1} + \beta_2 ecl_{t-1} + \beta_3^+ tc_{t-1}^+ + \beta_3^- tc_{t-1}^- + \\ &\sum_{j=1}^{p-1} \lambda_{0j} \Delta fa_{t-j} + \sum_{j=0}^{q-1} \left(\lambda_{1j} \Delta ep_{t-j} + \lambda_{2j} \Delta ecl_{t-j} + \lambda_{3j}^+ \Delta tc_{t-j}^+ + \lambda_{3j}^- \Delta tc_{t-j}^- \right) + \varepsilon_{2t}\end{aligned} \tag{3}$$

In equation (3), Δ and ε_{2t} denote, respectively, the first differences and the residual terms. The optimal numbers of lags that could be fixed by the Akaike information criterion (AIC) are denoted by *p* and *q*. The constant term is c_2, the long-run time trend coefficient is α, and β_0 is the error correction term that ought to be negative. Long-run estimates are β_0, β_1, β_2, β_3^+, β_3^- and short-run estimates are $\lambda_{ij}, \lambda_{3j}^+, \lambda_{3j}^-$. Long-run coefficients are equal to $-\beta_1/\beta_0, -\beta_2/\beta_0, -\beta_3^+/\beta_0, -\beta_3^-/\beta_0$. We check the robustness of our computations by normality, heteroskedasticity, and serial correlation tests. We validate short- and long-run asymmetries by means of the Wald test. The null hypothesis is $-\beta_3^+/\beta_0 = -\beta_3^-/\beta_0$ for long-run asymmetry, and we can use the null hypothesis $\sum_{j=0}^{q-1} \lambda_{3j}^+ = \sum_{j=0}^{q-1} \lambda_{3j}^-$ for short-run asymmetry.

To assess long-run cointegration between variables, Pesaran et *al.* (2001) compare the estimated Fisher-statistic (F) of the Wald test with a lower value (LV) and an upper value (UV) leading to three possible conclusions: *a)* if F>UV, variables are long-run cointegrated; *b)* if F<LV, there is absence of long-run cointegration between variables; *c)* if LV≤F≤UV, this test is inconclusive.

Estimates of our NARDL model are gathered in Table 3. The Fisher statistic is higher than the upper bound of the 1% significance level, and the error correction term (ECT) is negative and significant at the 5% level, implying a long-run cointegration between ethanol production, exports of crops and livestock, partial sums of increases in temperature change, and partial sums of decreases in temperature change. Residues are not serially correlated, are homoskedastic, and are normally distributed. Both R-squared and adjusted R-squared are higher than 0.9, signifying that the global estimate is very good. All our long-run coefficients are statistically significant at the 1% level, except the long-run coefficient of partial sums of decreases in temperature change, which is not significant. The majority of short-run coefficients (7 out of 12) are significant. The Wald tests reject the null hypothesis of equating the long-run coefficients, and that of the joint long- and short-run coefficients.

Table 3. NARDL estimates

Conditional error correction results		
Exogeneous variables	Coefficient	Prob.
fa_{t-1}	-0.368184[b]	0.0154
ep_{t-1}	-0.010092[a]	0.0018
Ecl_{t-1}	-0.010490[b]	0.0323
tc^{+}_{t-1}	-0.037969[a]	0.0021
tc^{-}_{t-1}	-0.000167	0.9666
trend	0.004396[a]	0.0019
Δep	0.000725	0.7421
Δecl	-0.014678[a]	0.0023
Δecl_{t-1}	0.007195[c]	0.0574
Δecl_{t-2}	-0.010939[a]	0.0006
Δtc^{+}	-0.007026[b]	0.0133
Δtc^{-}	-0.002080	0.3270
Δtc^{+}_{t-1}	0.020940[a]	0.0068
Δtc^{-}_{t-1}	0.004149	0.1315
Δtc^{+}_{t-2}	0.009844[b]	0.0481
Δtc^{-}_{t-2}	0.000803	0.7223
Δtc^{+}_{t-3}	-0.003543	0.1601
Δtc^{-}_{t-3}	0.010539[a]	0.0013
constant	5.902711[b]	0.0156
Cointegrating coefficients (restricted trend)		
Exogeneous Variables	Coefficient	Prob.
ep_{t-1}	-0.0274[a]	0.0033
Ecl_{t-1}	-0.0285[a]	0.0000
Tc^{+}_{t-1}	-0.1031[a]	0.0000
Tc^{-}_{t-1}	-0.0004	0.9663
trend	0.0119[a]	0.0000
R-squared=0.9712		

Adjusted R-squared=0.9136		
Optimal lags : (1,1,3,4)	Normality test: 0.8185	W_{LR}=12.9061(0.0058)[a]
Fisher statistic: 22.2631[a]	LM test: 0.5604	$W_{SR=}$ 0.3752(0.5554)
$ECT_{t-1=}$ -0.3682[b]	BPG test: 0.3049	W_J=10.7836(0.0041)[a]
Cointegration: yes		

The Fisher statistic is calculated for the case of a restricted trend. Critical values are taken from Pesaran *et al.* (2001) for a finite sample n=30. The maximum number of lags chosen for the dependent and independent variables is 1 and 4, respectively. Optimal lags are picked by the Akaike information criterion. Diagnostic tests include serial correlation LM (Breusch-Godfrey), heteroskedasticity (Breusch-Pagan-Godfrey(BPG)), and normality (Jarque-Bera); the probabilities of rejecting the null hypotheses are given. The LM test is computed with lag=1. W_{LR}, W_{SR}, and W_J are the Fisher statistics of the Wald test for long-run, short-run, and joint (long- and short-run) asymmetries, respectively.
Statistical significance levels at 1%, 5%, and 10% are denoted by [a], [b], and [c], respectively.

Non-linear ARDL models incorporate three broad types of asymmetry: long-run or reaction asymmetry ($\beta_3^+ \neq \beta_3^-$), impact asymmetry related to the coefficients on the contemporaneous first differences ($\Delta tc^+ \neq \Delta tc^-$), and adjustment asymmetry. The latter arises from the simultaneous interaction of reaction and impact asymmetries with the error-correction coefficient. The cumulative dynamic multipliers describe the adjustment path from the initial equilibrium to the new equilibrium. The cumulative dynamic multiplier effects of tc_t^+ and tc_t^- on fa_t can be estimated as:

$$m_h^+ = \sum_{i=0}^{h} \frac{\partial fa_{t+i}}{\partial tc_t^+} \quad , \quad m_h^- = \sum_{i=0}^{h} \frac{\partial fa_{t+i}}{\partial tc_t^-} \quad , \quad h = 0, 1, 2, \dots \tag{4}$$

We note that when $h \to +\infty$, then $m_h^+ \to \beta_3^+$ and $m_h^- \to \beta_3^-$. These dynamic multipliers are illustrated graphically in Fig. 2.

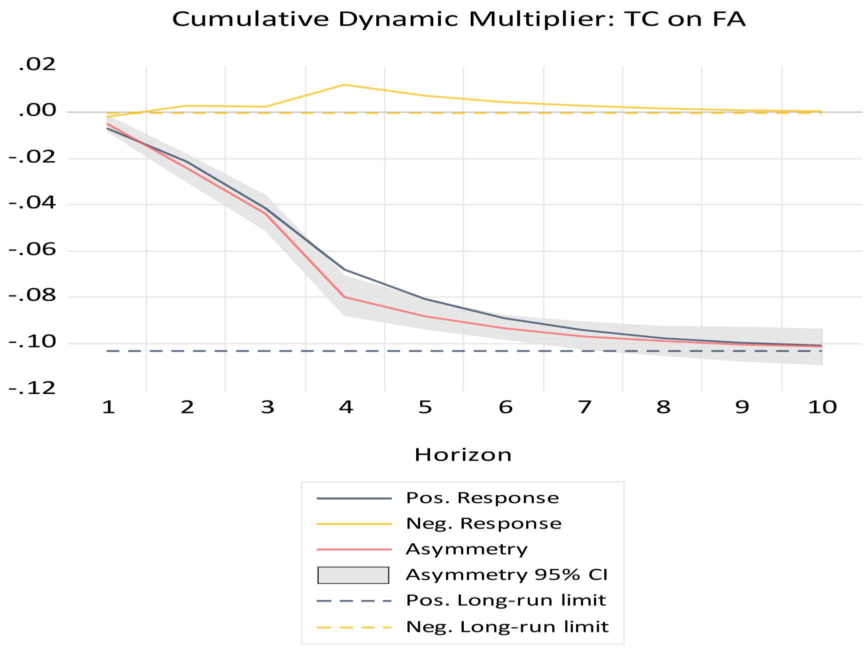

Fig. 2. Cumulative dynamic multiplier: TC on FA

Brown et *al.* (1975) presented the statistics cumulative sum (CUSUM) and the cumulative sum of squares that ensure the stability of long-run estimated coefficients. The estimated parameters of a regression can be considered as stable when the plots of these statistics fall inside the 5% critical constraints. These statistics are, in fact, within the crucial values of the 5% level of significance, as our Fig. 3 demonstrates. Our long-term NARDL calculated coefficients are hence steady.

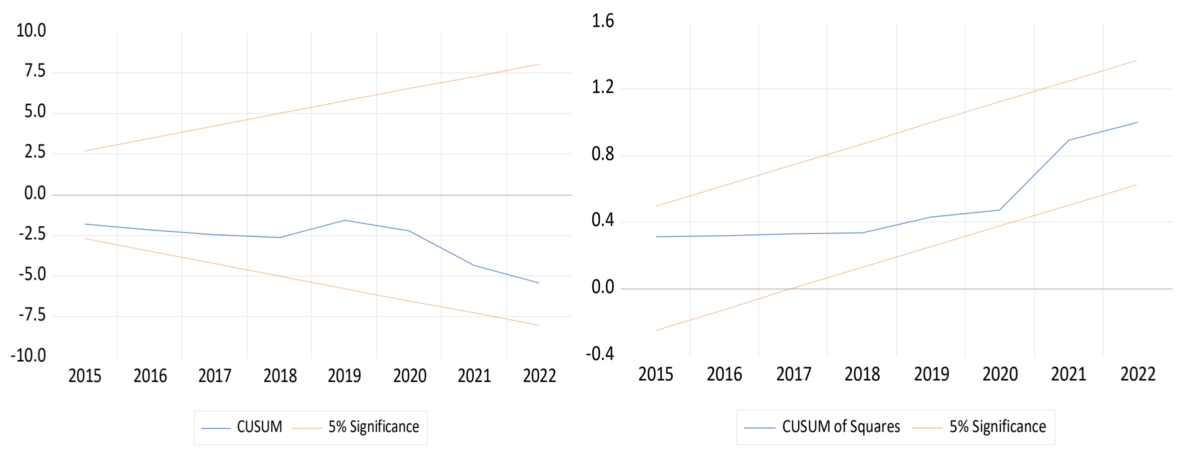

Fig. 3. CUSUM and CUSUM of Squares of recursive residuals

5. Discussion of the results

Table 3 shows that all our long-run coefficients are negative and statistically significant at the 1% significance level, except for that of decreases in temperature change. An increase in ethanol production of 1% reduces Brazil's forest area by 0.03%. While this elasticity is not very high, the negative impact is very worrying because the annual increase in ethanol production is important (136% between 1990 and 2022), and Brazil's forest area is considerable. It means that forests are cut down to expand biofuel ethanol production cultures, such as sugar cane. Our result is similar to that of Pablo-Romero *et al.* (2023) research on 19 Latin American and Caribbean countries, showing that energy consumption per capita decreases forest area per capita, but differs from that of Aydin *et al.* (2024) study on Finland, concluding that Biomass energy consumption has a non-significant impact on forest footprint. Our contribution is worth considering, as it is the first econometric research evaluating the impact of ethanol production on Brazil's forest area.

A 1% increase in exports of crops and livestock reduces Brazil's forest area by 0.03%. Again, while this elasticity is weak, the negative impacts of increasing ECL may be dramatic because exports of crops and livestock have realized a very significant increase (700% between 1990 and 2022), and Brazil's forest area is very important. It means that forest area is being cut for expanding pasture and crops whose production is intended for export. Knowing that the majority of crops and livestock production in Brazil is destined for exports, our result is similar to some panel studies on municipalities in Brazil recommending that soybean and cattle production may promote deforestation (Carvalho and Domingues, 2016; Faria and Almeida, 2016). However, our results differ from some other Brazil's municipalities panel studies suggesting that cattle farming reduces deforestation (Sousa *et al.*, 2022), or those indicating that municipalities with higher and more consistent soybean production that was not destinated for exports were more strongly linked to deforestation (Silva *et al.*, 2023), or those showing that the impacts of the new soy technology on deforestation are lessened by trade with China (Carreira *et al.*, 2024). Our contribution is interesting as it is the first econometric study explicitly evaluating the impact of exports of crops and livestock on the forest area of Brazil.

The long-run coefficient of the partial sums of increases in temperature change is negative and significant at the 1% level, whereas that of decreases in temperature change is infinitesimally negative and not statistically significant. This means that temperature increases reduce forest area for sure, but temperature reductions do not guarantee the recovery of lost forests. An increase in temperature change of 1°C results in the long-run to an important and very worrying reduction of Brazil's forest area by nearly 9.8%. This catastrophic scenario has a very high realization probability because during our considered period, 1990 to 2022, temperature change has evolved from a minimum value of 0.39°C realized in 1992 to a maximum value of 1.6°C realized in 2015. Here, we have a complex puzzle because temperature change, which is due to human activity generating harmful gases as greenhouse gases, and perhaps to also some natural change in the atmosphere, reduces forest areas, and this last reduction in forest areas itself is responsible for more GHG accumulation in the atmosphere and an increase in temperature. Our results are in line with some studies based on climate change scenarios as Lapola *et al.* (2011) preventing that a severe regional climate change would result in an expansion of deforestation by 20% (181000 km^2) in the Amazon and of 273% (240000 km^2) in the Cerrado, and Munday *et al.* (2025) recommending that lowering global temperatures below 1.5°C enables to reduce long-term forest loss. The contribution of our study is worth considering because of the absence of an econometric study about the impact of climate change (or temperature change) on forest area or deforestation.

Looking at the short-run coefficients of Table 3, we can see that the contemporaneous coefficient of cumulative increases in temperature change is negative and significant at the 5% level, meaning that an increase in temperature change has an immediate negative impact on forest area. However, the contemporaneous coefficient of cumulative decrease in temperature change is not significant. The cumulative dynamic multiplier graph of Fig. 2 shows that a shock to the positive increase in TC reduces forest area rapidly until period 4, and after that, the system moves to the long-run equilibrium. A shock on the negative increase in temperature change has a moderate positive and beneficial impact during the first three periods, and this impact is very pronounced during the fourth period, then its impact disappears slowly, and the system moves to the long-run equilibrium. In all cases, innovation shocks on a positive increase in TC dominate those of a negative increase in TC.

6. Conclusion and policy recommendations

This paper evaluates the long-run impact of fuel ethanol production and exports of crops and livestock on the forest area in Brazil. We also evaluate the asymmetric impact of temperature change on forest area by using the non-linear autoregressive distributed lag model. Annual data between 1990 and 2022 are used for this purpose.

An increase in ethanol production importantly reduces the forest area in Brazil. In fact, forest areas are cut down in favour of cultures for biofuel ethanol, such as sugar cane. Our contribution is interesting, as it is the first econometric research estimating the impact of ethanol production on Brazil's forest area.

Also, the expansion of exports of crops and livestock importantly reduces Brazil's forest area. This is due to the fact that increasing exports of crops and livestock implies a cut in forest area to increase land areas destined for pasture and crops. Again, this result is worth considering because it is the first econometric study explicitly evaluating the effect of exports of crops and livestock on Brazil's forest area.

We demonstrate that while rising temperatures do reduce forest area in the long-run, falling temperatures do not guarantee the regeneration of lost forests. A temperature increase of 1°C leads in the long term to a significant and very worrying reduction in the forest area of Brazil, of almost 9.8%. This negative impact is more pronounced because a reduction in forest area reduces the GHG absorbed and is responsible for increasing temperatures. Temperature change increase has an immediate negative impact on forest area, while the immediate impact of a decrease in temperature change is not guaranteed. Cumulative dynamic multiplier shocks on increases in temperature change importantly reduce forest area until the fourth period, and then the system moves to the long-run equilibrium. Also, the cumulative dynamic multiplier shock on decreases in temperature change has a moderate positive impact on forest area during the first three periods, and a more pronounced positive impact during the fourth period, then the system moves to the long-run equilibrium.

Innovation shocks on positive increase in temperature change always dominate those on negative increase in temperature change. Our contribution is interesting due to the absence of econometric research concerning the impact of climate change (or temperature change) on forest area or deforestation.

Given our econometric results, we can draw some policy recommendations: *i)* Brazil has developed a strategy for fuel ethanol production to reduce GHG emissions and to ensure its energy security with respect to fossil fuels. Since fuel ethanol production reduces forest area, the Brazilian government should encourage research and development (R&D) and innovation in renewable energy (e.g., solar, wave), and especially in second-generation or third-generation biofuels production. Competitive credits for installing the required production capacities and subsidies may be considered. Tan *et al.* (2008) propose strategies for making second-generation biofuel (cellulosic ethanol) the major biofuel in the World, and Ben Jebli and Ben Youssef (2019) recommend this strategy to reduce the substituability between agriculture and biofuel production in Brazil; *ii)* To reduce the negative impact of exports of crops and livestock on forest area, the Brazilian governement should encourage agricultural research to increase agricultural yields and the use of aeroponics for vegetable culture or smart agriculture because this will lead to less pressure on agricultural lands and therefore on deforestation. Also, by preserving and even recovering forest areas, eventual losses from exports of crops and livestock can be largely recuparated from tourists receipts if appropriate strategy for encouraging green tourism is adopted; *iii)* To reduce temperature increases, which are mainly caused by global GHG emissions, Brazil can contribute by reducing its own GHG in using more clean renewable energy sources as solar energy or wave power. Encouraging R&D and innovation in energy efficiency and renewable energy through appropriate policies and subsidies is recommended.

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