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An Empirical Investigation into Greenhouse Gas Emissions and Agricultural Economic Performance in Baltic Countries: A Non-Linear Framework

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Abstract: The EU's Common Agricultural Policy has for decades been geared towards sustainable agricultural development, not only to ensure a fair income for farmers but also to tackle climate change and environmental degradation, emphasizing the link between agricultural economic activity and the importance of greenhouse gas (GHG) emissions. The importance of research in this area is reinforced by the EU's ever-increasing sustainability ambitions in recent years, as set out in the European Green Deal, which has found a place in the new 2023–2027 Common Agricultural Policy (CAP) policy to meet the EU's 2050 target to achieve climate neutrality. The aim of this study is to assess the relationship between greenhouse gas emissions and economic performance for the agricultural sector in the Baltic States (Lithuania, Latvia, and Estonia) from 1998 to 2019. These three countries have similar agricultural structures and similar natural conditions, so the research provides comparable results. The relationship was analyzed by using the nonlinear autoregressive distributed lag (NARDL) model that allows the estimation of short-term dynamics using a distributed delay component and long-term dynamics using a single cointegrating vector. The analysis of the research data showed that gross value-added changes influence greenhouse gas emissions in all three countries. The results of the research, on the other hand, suggested that there is evidence supporting the reverse 'U-shaped' impact of the environmental Kuznets curve (ECK) when assessing data from Lithuania and Estonia, but not from Latvia. The study's findings have significant policy consequences.

Keywords: sustainable agriculture; negative externalities; GHG emissions; NARDL model

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1. Introduction

Climate change and environmental degradation pose an existential threat not only to Europe, but also to the whole world. The Intergovernmental Panel on Climate Change (IPCC) predicts that, unless urgent action is taken, global temperatures could rise further by 1.8–4 °C by 2100. This means that, compared to pre-industrial levels, the temperature rise would be more than 2 °C [1].

In addition to natural climate change, human activities may be responsible for long-term global warming of more than 1.5 °C [2]. The interaction between climate change and agriculture is recognized as a two-way relationship [3]. Therefore, agriculture both contributes to and is affected by climate change [4]. It is the second largest sector that contributes directly and indirectly to global warming and climate change through the release of greenhouse gases [5–8]. According to statistics [9], agriculture accounts for 10.3% of the EU's greenhouse gas emissions in CO_2 equivalents (2019), and their greatest sources are enteric fermentation, manure deposited on pasture, synthetic fertilizer, paddy rice cultivation, and biomass burning. Agriculture in particular releases significant amounts of methane (produced by livestock during digestion due to enteric fermentation as well as from stored manure) and nitrous oxide (which is a product of nitrogen fertilizers) [4]. In the EU, agricultural emissions were 20.9% lower in 2019 than they were in 1990 [9]. This was due to fewer livestock, more efficient use of fertilizers, better management of manure, and more advanced methods being used in production. On the other hand, research confirms the impact of climate change on farming performance. If negative effects of climate change on crop yields have been more common than positive ones [10], they have become even worse in recent years [2]. Changes in rainfall and water endowments, temperature, high heat, and other climatic conditions have an impact on crop yield and income of farm families [11]. According to the Intergovernmental Panel on Climate Change (IPCC), the effects of climate change on agricultural productivity around the world not only affect the income and living standards of people who work in agriculture but also lead to poverty, food insecurity, and agricultural development that is not sustainable [2].

Various solutions for solving climate change problems are examined. One of them is further economic growth, which can change the population's tendency to use environmentally polluting sources and mobilize resources for the implementation of environmental protection programs. The environmental Kuznets curve (EKC) concept is often used in the literature to evaluate how economic expansion affects environmental quality [12]. However, many nations—such as those in the Baltic region—have not yet been thoroughly investigated.

The aim of this study is to assess the linkages between environmental damage due to agricultural greenhouse gas emissions and agricultural economic performance in Baltic countries. The topic is examined in three Baltic countries—Lithuania, Latvia, and Estonia—which have a comparable agricultural structure and environmental circumstances and are subject to the Common Agricultural Policy. These nations have a historical–political identity as well: (i) they were all seized by the USSR in the 1940s; (ii) they regained independence in 1990–1991; (iii) they joined the EU in 2004; and (iv) they are Eurozone members. Agriculture is also one of the most traditional economic sectors in Estonia, Latvia, and Lithuania, producing food not only for the residents of these nations but also for other countries, as well as addressing employment and other social and environmental protection concerns.

This study consists of five main parts. In the present section, the authors have revealed the links between agricultural economic performance and greenhouse gas emissions and the instruments used to measure these links, and a short analysis of the theoretical background is given. In Section 2, the authors describe their research methods and used data. Section 3 provides the results of empirical research. The last two sections of this paper are the discussion and general conclusions that are drawn from the scientific literature and the analysis of empirical research.

Economic growth contributes to greenhouse gas (GHG) emissions from various economic activities, including agriculture. By contributing to the United Nations Sustainable Development Goals (the UN SDGs), the EU has committed itself to achieving the 2050 target, at which point its impact on the climate would become neutral. Communications from the European Commission "The European Green Deal" [13], "A Farm to Fork Strategy" [14], "The EU Biodiversity Strategy for 2030" [15], "The New Circular Economy Action Plan" [16], new Common Agricultural Policy (CAP) instruments, and other initiatives and actions contribute to the 2050 agenda and the goal of climate neutrality. About 10% of the GHG emissions in the EU come from agriculture [9], which also helps reduce GHG emissions through green targets.

The link between economic growth and environmental quality has long been debated. The first to draw attention to this problem were Grossman and Krueger (1991) [17], Beckerman (1992) [18], Panayotou (1993) [19], and Grossman and Krueger (1995) [20]. In their research, they have found that economic growth degrades the quality of the environment in the early stages, but that economic growth continues to lead to an improvement in the quality of the environment. The link between income (a potential indicator of economic growth) and pollution can be explained by three factors: technology, composition, and scale [21]. The scale effect is when there is a transition from an agrarian to an industrial economy. As the economy develops, environmental pollution increases and its quality deteriorates. The composition effect occurs during the structural changes of the economy—i.e., moving from agrarian to industrial, then from industrial to a service economy. The technology effect is related to the progress of technology. As the economy grows and technology is improved, pollution goes down [21].

Given the recent challenges related to climate change and increasing GHG emissions, scientists and researchers are investigating the link between CO_2 emissions and economic growth to determine whether the latter can have a positive impact on pollution [22]. The Kuznets curve hypothesis is often used to explain and measure these relationships [23]. It is also very important for making policies about climate change and coming up with plans for sustainable economic development [24]. The interaction between economic growth and environmental pollution in testing the validity of the environmental Kuznets curve (EKC) hypothesis has been studied in various aspects by various scientists and researchers in various sectors and countries [21,23,25–39]. Various methods have been used to determine these causal relationships: decomposition methods [38], the Johansen cointegration test, the Granger causality test, impulse–response and variance decomposition analysis of vector autoregression models (VAR) [25], semiparametric spatial autoregressive models, the spatial lag model (SLM), the spatial autoregressive model with spatial autoregressive disturbances (SARAR), two-stage least squares regression (2SLSR), quantile regression (QR) and nonparametric regression (NPR) [32], the heterogeneous panel causality method [24], the interactive fixed effect (IFE) and dynamic common correlated effect (D-CCE) [39], the autoregressive distributed lag (ARDL) method [28–30,35,40–43], dynamic ordinary least squares (DOLS) and fully modified ordinary least squares (FMOLS) methods [33,34,43,44], the generalized method of moments (GMM) method [45], panel DOLS [46], the vector error correction (VECM) method [27,28,47], the canonical cointegrating regression (CCR) method [43], and spatial error model (SEM) [31].

The Kuznets curve of the environment hypothesizes that there is a nonlinear inverted U-shape relation between environmental quality and economic growth [21,23,24,26,39]. According to this theory, the quality of the environment deteriorates to a certain point in the first stages of economic growth and—after the breaking point—the development of the economy leads to an improvement in the quality of the environment, thus creating an inverse U-shape relationship between economic growth and environmental quality [19,22]. In previous studies, this dependence has been tested using relatively short time series of data, but this should be considered a limitation of the studies [23]. Long-term annual time series for various pollutant statistics are only available in the United States and European Union member states [48] and therefore provide more data for research than in other countries where data are incomplete or missing. In the absence of reliable and available statistics, CO_2 emissions that are harmful to human health and the environment are generally considered to be an indicator of environmental degradation [21,22,39,49], less frequently the emission of toxic pollutants such as heavy metals [23], the ecological footprint [24,39], air and water quality indicators [50], and various other environmental indicators. Most of the time, gross domestic product, gross domestic product per capita, real gross domestic product per capita, income level, or income per capita are used to measure economic growth [24,51,52]. Some studies have confirmed a positive or negative relationship between environmental pollution (measured in global emissions by GHG emissions) and economic growth [27,29–31,33,34,36,40,45,46,53,54], not found by others [28,35,36,41–44,47]. This is mostly due to the use of different survey methods and data time series and the fact that CO_2 emissions have no local or regional effects on the environment [21,22,55–58]. However, it is important to note that global GHG emissions are linked to global climate change, global warming, depletion of the ozone layer, and global warming, and have less impact on the environment of the area where they are emitted [21]. As a result, countries are working to reduce GHG emissions, often through policy tools, and thus to reduce threats to human health and the environment. This reinforces the importance and necessity of research in this area.

2. Materials and Methods

2.1. Methods

Figure 1 presents the schematic overview of the research. The research employs two variables: greenhouse gases (GHG) and the gross value added generated by agriculture (GVA). The carbon emission equivalent measures the amount of greenhouse gases in tons produced in a CO_2 equivalent. This variable was chosen as the best indication of environmental harm caused by a range of gases generated in agriculture and has been utilized in recent studies [59]. The latter variable represents net agricultural value added in thousands of purchasing power standards (PPS). As a replacement for agricultural income, gross value added at basic prices allows for a more thorough comparison of three nations.

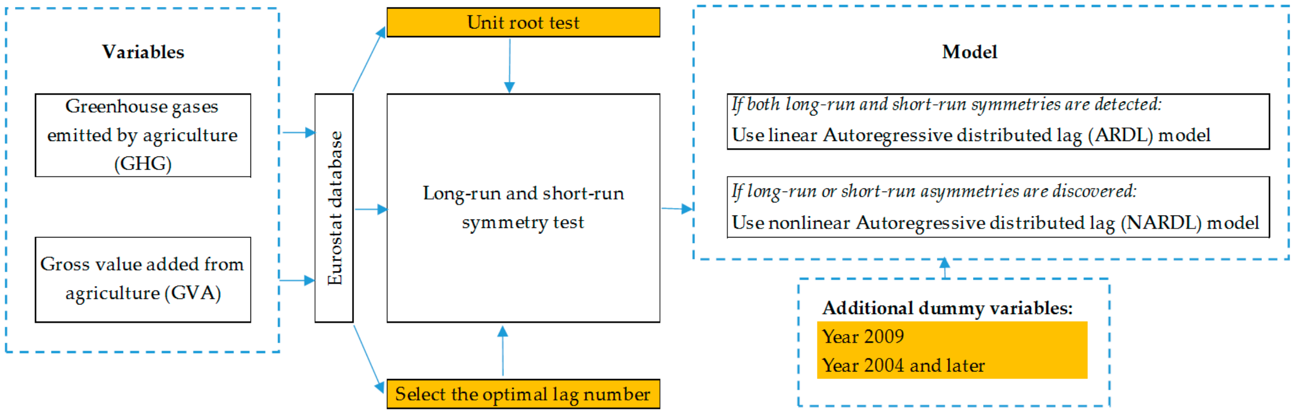


Figure 1. Framework of the research.

Next, methods to show relationships between time series of greenhouse gases (GHG) and the gross value added from agriculture (GVA) are described. An error correction model (ECM) is frequently used by other authors to investigate variables (time series) that together have a long-term stochastic trend and form an equilibrium [60]. In addition, improved ECM techniques that leverage asymmetric effects and model time series with varied orders of integration may also be employed. In most studies, when causality and linear cointegration confirm that the dependent variable is expected to respond in a symmetric way to increases and decreases of the independent variable, the authors employ the linear unrestricted error correction model [59].

As a result, an autoregressive distributed lag (ARDL) model is used in this research, which is based on an ordinary least square (OLS) based model that is like the ECM technique but is applicable to both non-stationary and mixed order of integration time series [61]. In the ARDL model, there are long-turn and short-term effects and their impacts on the first level difference on the dependent variable, in this case, greenhouse gas emissions (Formula (1)). Because all of the long-run connection variables are described but not constrained, the ARDL model is a kind of unrestrained ECM.

$$\Delta GHG_t = \mu + \rho GHG_{t-1} + \theta GVA_{t-1} + \sum_{i=1}^{p}(a_i \Delta GHG_{t-1}) + \sum_{i=0}^{q-1}(\omega_i \Delta GVA_{t-1}) + \varepsilon_t, \quad (1)$$

where *GHG* is the carbon emission equivalent; *GVA* is the gross value added from agriculture; μ, ρ, θ, α, ω are model parameters; εt is the residual error; Δ is the change in the first order; i is the time lag; p and q are number of time lags; and t is the time.

The underlying research problem, as stated in the introduction, places a high value on asymmetries. Hence, the non-linear autoregressive distributed lag (NARDL) model is used to model cointegration, non-linearities, and causation at the same time (Formula (2)).

The distributed lag nonlinear autoregressive distributed lag (NARDL) model is a single-equation error correction model that uses positive and negative partial sum decompositions of the explanatory variables to add short- and long-run nonlinearities [62]. In other words, using partial sum decompositions of the independent variable, this technique assesses the asymmetry in the long-run equilibrium relationship as well as the short-run dynamic coefficients. Therefore, the gross value added (GVA) is broken down into its positive and negative parts.

Another important step is to select the optimal lag numbers p and q. Therefore, the following information criteria are used to select the best model: the Hannan–Quinn information criterion, the Akaike information criterion, and the Schwartz information criterion (Bayesian). This means that the information criteria values need to be the lowest to choose the best model with the right number of lags.

Time dummies can be added to this equation as well to better explain the long-term dynamics of greenhouse emissions and the gross value added by the agricultural sector. Time dummies show how many years have passed since some countries joined the European Union, as well as the financial crisis of 2009, which is defined by an impulse dummy.

$$\Delta GHG_t = \mu + \rho GHG_{t-1} + \theta^+ GVA^+_{t-1} + \theta^- GVA^-_{t-1} + \sum_{i=1}^{p}(a_i \Delta GHG_{t-1}) + \sum_{i=0}^{q-1}\left(\omega_i^+ \Delta GVA^+_{t-1} + \omega_i^- \Delta GVA^-_{t-1}\right) + \varepsilon_t, \quad (2)$$

where GHG is the carbon emission equivalent; GVA^+ is the sum of positive changes in gross value added from agriculture; GVA^- is the sum of negative changes in gross value added from agriculture; μ, ρ, θ^+, θ^-, α, ω^+, and ω^- are model parameters; ε_t is the residual error; Δ is the change in the first order; i is the time lag; p and q are number of time lags; and t is the time.

The methods described above may be used to see whether GVA has symmetric or asymmetric effects on GHG in the short and long term. Traditional ARDL may be employed for improved explanatory and prediction power of long- and short-term effects if there is no statistically significant asymmetry and calculated p-values are above 0.10. The hypothesis for long-run asymmetry in the NARDL model is

$$\mathrm{H}_0: \ \theta^+ = \theta^-, \quad (3)$$

Then, the hypothesis for short-run asymmetry can be described as

$$\mathrm{H}_0: \ \sum_{i=0}^{q-1}(\omega_i^+) = \sum_{i=0}^{q-1}(\omega_i^-), \quad (4)$$

Further analysis can be performed after the selection between models ARDL and NARDL is made. Besides estimations for each individual parameter in the formula, the paper involves additional hypotheses. As mentioned above, the model uses a different number of time lags. Therefore, combined hypotheses for all lags can be tested as well, such as h_0: $a_1 = a_2 = 0$.

It can also be tested if all short-term or long-term effects are significant or not. Whether all parameters of long-run or short-run coefficients are equal to zero. This extends the research into the fact that if both time series are cointegrated, they can explain one another.

To test hypotheses such as these, it is necessary to omit certain variables from the ARDL equation using the Wald test based on the covariance matrix [63]. This re-estimates the supplied model after excluding the selected variables. It provides a test for the joint significance of the missing variables in addition to the standard model output. The null hypothesis states that all the missing variables' actual coefficients are zero.

It is critical to pay close attention to whether long-run effects are significantly different from one another, and thus a test is performed to determine whether the difference between variables is equal to zero:

$$H_0: \ \rho = \theta, \tag{5}$$

As a result, the real influence of *GVA* through parameter θ must be calculated, taking into account the magnitude and order of the dependent variable *GHG* through parameter ρ. To obtain a long-run coefficient, an additional approximation must be made, defined as a division between variables (Formulas (6) and (7)). The long-run effect of *GVA* on *GHG* is shown in the upper portion. The weight associated with the autoregressive structure's reaction is represented by the bottom component [64,65].

Next, the estimations for both the coefficient and p-value for this multiplier are provided as

$$L^{+} = -\frac{\theta^{+}}{\rho}, \tag{6}$$

$$L^{-} = -\frac{\theta^{-}}{\rho}, \tag{7}$$

where L^{+} and L^{-} are positive and negative long-run coefficients; and θ and ρ are NARDL model parameters from Formula (2).

If further analysis leads to the selection of the NARDL approach, then the corresponding coefficients should be used: the long run coefficients L^{+} and L^{-} as in other studies [59].

Next, the study employs many years, thus potential structural breaks should be taken into consideration as well. A structural break is an unanticipated change in the parameters of regression models over time in econometrics and statistics. This may lead to significant forecasting mistakes and model unreliability in general, as well as changes in the underlying processes.

The Quandt likelihood ratio (QLR) test may be employed when the break date is unclear [66]. It is often used in research for structural breaks. It is a modified version of the Chow test that employs the greatest of all F-statistics produced when the Chow test is applied to all potential break dates within a given range [67]. The analysis uses the default 15 percent trimming to see at which observation the maximum value of the F statistic occurs. The asymptotic p-value for chi-square is estimated to measure the likeliness of this structural break. Next, the 5 percent QLR critical value is observed.

Typical methods for time series analysis are used as well. When analyzing time series, it is crucial that their statistical characteristics and distribution—autocorrelation, mean, and variance—stay consistent. Therefore, a unit root test based on the enhanced Dickey–Fuller approach is utilized with and without a time trend [68]. In addition, time series cointegration is investigated using the Engle–Granger cointegration test [69]. If two or more time series have the same stochastic drift, they are cointegrated. In other words, if both time series are non-stationary and have a common trend, they are said to be cointegrated. The stages in the Engle–Granger cointegration test are as follows: the Dickey–Fuller test is used to determine whether each of the provided variables has a unit root; the cointegrating regression is calculated; and the residuals are evaluated using the augmented Dickey-Fuller (ADF) test.

The null hypothesis of normal distribution is tested using the normal distribution of residuals (NORM) test. Running the ARDL model assumes that the residuals are normal. If the residuals are normally distributed and this assumption is correct, then model inference (confidence intervals and model predictions) should be correct as well.

A unit-root test using the ADF test model with and without trend to test if residuals from the ARDL and NARDL models which are stationary should be performed as well. Because the residuals are normally distributed and behave well, the test's performance for every given sample will be influenced by the dynamic model's quality and sample size. To prevent erroneous regressions in a time series environment, residuals must be stationary.

Next, the test for autoregressive conditional heteroskedasticity (ARCH) is performed. The null hypothesis is that there is no ARCH effect. In other words, ARCH effects are evident if the squared residuals/errors of the ARDL time series model show autocorrelation. The ARCH effect is defined as a correlation between the volatility of a time series, as measured by conditional variance, and its previous values or innovations. As a result, this indicates whether residuals are clustered.

To increase the number of observations and to achieve more precise results, panel data analysis is employed as well. Panel data may be used to represent different nations' shared behaviors. Pure time series data have less information, variability, and efficiency than panel data. The Baltic states statistics panel includes all three countries. The structure of the dataset consists of stacked time series and the number of cross-sectional units is 3. The number of time periods is 21. However, the panel data approach does not provide an opportunity to perform the ARCH and QLR tests.

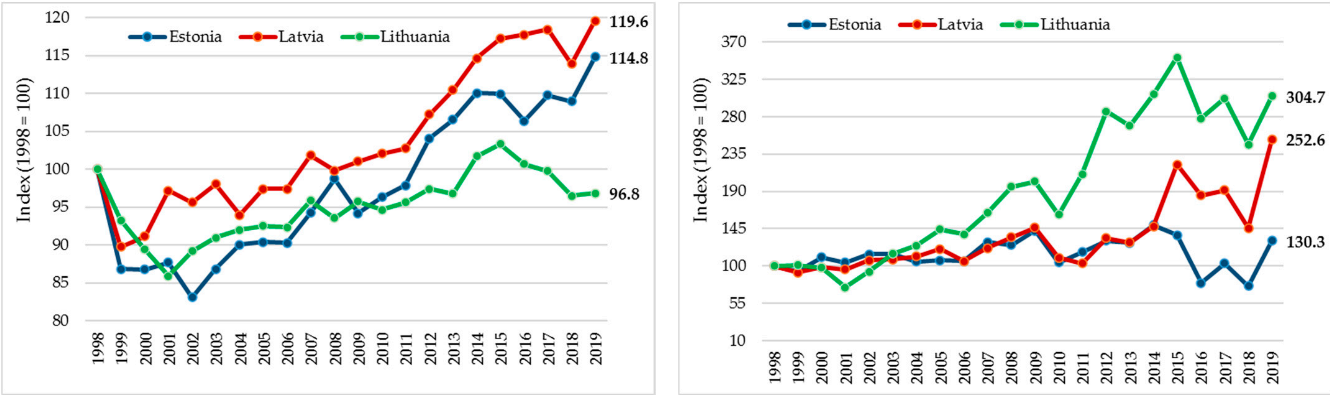
2.2. Data Sources

Using data from three EU countries, the study investigates the relationship between carbon emissions equivalent and gross value added from agriculture. More specifically, it investigates how gross value added in agriculture affects greenhouse gas emissions in Lithuania, Latvia, and Estonia. Eurostat [70] provides the study with yearly carbon emissions equivalent and gross value added generated by agriculture. The gross value added from agriculture is taken from the economic accounts for agriculture. To ensure comparability over time and space and to eliminate price and exchange rate differences, this indicator is measured in purchasing power standards (PPS) at the basic constant prices of 2010. The data on GHG emissions from agriculture in tones of CO_2 equivalent come from the Eurostat database, more specifically the greenhouse gas emissions by source sector statistics. The data cover the years 1998 to 2019.

3. Results

In all Baltic nations, agriculture is a significant economic sector. According to the 2020 Agricultural Census [71], Lithuania had the most farms (132,076), 64 percent more than Estonia and Latvia combined, although its average farm size was the lowest (23.4 ha by land area). In contrast, there were the fewest farms (11,369) in Estonia, despite the fact that their average size was over four times larger than that of Lithuania (106.5 ha). Similarities could be seen in the agricultural structures of Estonia and Latvia: more than half of the total crop area was made up of cereals, followed by forage crops (about a quarter) and industrial plants, which made up the remaining 11 percent. Cereals made up 63.9 percent of Lithuania's total crop area, followed by industrial plants (13 percent), forage crops (11.9 percent), and leguminous crops (6.9 percent). A quarter of all farms in Estonia were focused on raising livestock. In Latvia and Lithuania, such farms accounted for 18 and 15.2 percent of the total, respectively. The investment growth of farms, including the use of public assistance, is given considerable attention in all of the Baltic nations, although the contribution of farms to environmental protection is still minimal. The authors who tested the EKC hypothesis in the Baltic countries emphasize that these countries are heavily reliant on electricity imports and fossil fuel-based energy sources, and that country-level differences in fossil fuel dependence may result in the EKC hypothesis not being valid in some of the Baltic countries [12]. In order to lessen pollution, organic farming is more developed in Estonia (in 2020, it accounted for 22.41 percent of the total land used for agriculture, compared to 14.79 percent and 8.00 percent in Latvia and Lithuania). This share in 2004 was 7.2 percent for Estonia, 1.6 percent for Latvia, and 1.4 percent for Lithuania [72].

The analysis starts with descriptive data for all three nations and both variables (for time graphs see Figure 2; for descriptive statistics see Table 1). The mean value of the greenhouse gas emission equivalent is highest in Lithuania (4163.5) and lowest in Estonia (1275.3). Lithuania has the greatest mean value of gross value-added in agriculture (1354.3), while Estonia has the lowest (384.49). The volatility of both variables given by standard deviation can be ranked in the same order as their mean values.



(**a**) (**b**)

Figure 2. Baltic states time series: (**a**) Carbon emissions equivalent of greenhouse gases (GHG); (**b**) Gross value added generated by agriculture (GVA). Source: authors' calculations based on Eurostat [9,70] data, 2022.

Table 1. Descriptive statistics of carbon emissions equivalent of greenhouse gases (GHG) and gross value added generated by agriculture (GVA).

Indicators	**Lithuania**		**Latvia**		**Estonia**	
	GHG	**GVA**	**GHG**	**GVA**	**GHG**	**GVA**
Using initial value GHG and GVA:						
Mean	4163.5	1354.3	1917.9	464.68	1275.3	384.49
Median	4192.0	1332.8	1875.3	414.96	1255.8	382.58
Minimum	3767.4	506.66	1653.2	313.38	1083.4	254.66
Maximum	4530.0	2401.5	2202.4	861.58	1496.9	500.95
Standard deviation	190.25	584.55	175.67	147.37	127.85	64.157
Skewness	0.0026	0.1932	0.3256	1.3634	0.1955	−0.1944
Kurtosis	−0.3643	−1.3157	−1.2257	1.0238	−1.3683	−0.4070
Using first level difference ΔGHG and ΔGVA:						
Mean	−6.6457	66.529	17.179	24.782	9.1786	4.8552
Median	14.350	129.18	21.700	22.010	20.660	0.9000
Minimum	−296.50	−505.43	−188.39	−156.76	−171.71	−194.08
Maximum	216.89	515.23	111.02	365.26	80.990	183.26
Standard deviation	124.50	253.43	70.897	116.61	57.500	80.181
Skewness	−0.3896	−0.5128	−1.1834	1.2478	−1.5295	−0.4043
Kurtosis	−0.2208	−0.1116	1.5062	2.2555	2.7089	0.9219

Source: authors' calculations based on Eurostat [9,70] data, 2022.

First level differences for both variables show similar results. Positive first-level difference mean values (except for GHG in Lithuania) indicate that both greenhouse gas emissions equivalent and gross value added grew throughout the observation period. The difference in carbon emission equivalent is the most volatile in Lithuania (124.50) and the least volatile in Estonia (57.500). The difference in gross value-added is the most volatile in Lithuania (253.43) and the least volatile in Estonia (80.181).

A skewness value greater than 1 or less than −1 indicates that, in most cases, a moderately skewed distribution is observed. Kurtosis of less than 3 is recognized as a platykurtic distribution for all countries and both variables.

Following that, the results of the augmented Dickey–Fuller (ADF) test using two models, one with a constant only and the other with both a constant and a trend, are presented (see Table 2). When using absolute values, the *p*-value for all three countries and both ADF models is more than 0.05, indicating that these time series have a unit-root and are non-stationary. Engle–Granger cointegration test results show that only for Lithuania, time series are almost cointegrated without trend (p-value is 0.0532).

Table 2. Augmented Dickey–Fuller test and Engle–Granger cointegration test results.

Indicators	Lithuania			Latvia			Estonia		
	GHG	GVA	Coint.	GHG	GVA	Coint.	GHG	GVA	Coint.
Using absolute value, p-values:									
test with constant	0.5564	0.8179	0.0532	0.8900	0.9016	0.3138	0.9592	0.1645	0.9872
with constant and trend	0.3729	0.4032	0.1132	0.7633	0.4666	0.7850	0.1065	0.4852	0.3472
Using first level difference, p-values:									
test with constant	0.0169	0.0049	0.0239	0.1137	0.0088	0.1241	0.0022	0.0269	0.0034
with constant and trend	0.1345	0.0353	0.2430	0.3527	0.0473	0.3282	0.0128	0.1509	0.0576

Source: authors' calculations based on Eurostat [9,70] data, 2022.

Even though the unit root analysis shows that variables are not stationary at absolute value, these series become stationary after calculating the first level difference, except for GHG in Latvia (p-value is 0.1137) when using test with constant only.

The information criteria for all three countries are lowest when using one or two GHG time lags (denoted as p) and three GVA time lags (denoted as q) (see Appendix A). For Lithuania and Latvia, the further analysis uses two GHG time lags (p = 2), while for Latvia the analysis uses one (p = 1). For panel data, the analysis uses two GHG time lags (p = 2) and one GVA time lag (q = 1).

Next, the results of tests for hypotheses of long-term and short-term asymmetry with the chosen number of time delays are given (see Table 3). In Lithuania and Estonia, the long-run p-value is below 0.05, so the hypothesis for long-run asymmetry is accepted. In all other cases, the p-values are high—above 0.10—indicating a tight symmetry between these variables. Therefore, the further analysis uses the conventional ARDL model for Latvia and panel data. The NARDL model is used for Lithuania and Latvia, but only with the long-term asymmetric parameters GVA^{+} and GVA^{-}.

Table 3. Long-run and short-run symmetry test results.

Time Period	Long Run, p-Value	Short Run, p-Value	Conclusion
Lithuania	0.0221	0.5177	Only long run asymmetry
Latvia	0.1451	0.3413	No asymmetry
Estonia	0.0081	0.1820	Only long run symmetry
All three countries	0.1966	0.4688	No asymmetry

Source: authors' calculations based on Eurostat [9,70] data, 2022.

Next, dummy variables are added to the ARDL and NARDL models to better explain these relationships because the time span of more than 20 years includes important events that may have changed the underlying relationships between GHG and GVA.

More specifically, countries' environmental policies were altered because of their membership in the EU. For example, changes and reforms in the Common Agricultural Policy for EU members—including, among other things, increased concern about greenhouse gas emissions mitigation, economic growth, and the adoption of greening farming practices, as well as the extensive use of alternative energy sources in the farming process—led to the adoption of greening farming practices and the satisfaction of sustainability criteria [59]. The time dummy variable accounts for these impacts. Therefore, critical years, such as 2009, may influence the form and context of relationships between greenhouse emissions and gross value added as reducing production decreases greenhouse gas emissions. A decrease in revenue, on the other hand, reduces the ability to take steps that are good for the environment.

For all the reasons stated above, discovering and confirming the presence of dummy variables is a critical stage in the methodological process. To detect the presence of dummy variables, the ARDL/NARDL model is estimated with selected dummy variables, but then they are eliminated from the model if their p-value is above 0.10. Then the output models are compared to better describe the relationships between GHG and GVA.

As mentioned before, the hypotheses of asymmetry are more often rejected; therefore, the ARDL approach is used in more cases than NARDL. To be more specific, this not only tests the long-run and short-run null hypotheses but also estimates their coefficient values. The number of lags used is the same as in the preliminary NARDL model: the number of lags for the independent variable is three, whereas the number of lags for the dependent variable is one or two, depending on country. Other assumptions remain the same. The unit root analysis and cointegration tests show that the data used are fit for further modeling. This implies that the variables are integrated at order one and thereby signals a possible cointegration relationship among the variables. In the next step, the dummy variables are added to the calculation. These are the years when each country joined the EU and the year of the financial crisis in 2009.

The analysis begins with NARDL model estimations for Lithuania during 1998–2019. Both GHG (−1) and GVA (−1) have a statistically significant effect (see Table 4). The long-term effect hypothesis h_1 is rejected as well, which means there are significant long-term effects. However, the long-run negative coefficient L^- is larger than the positive L^+ but both are statistically insignificant.

Table 4. Nonlinear autoregressive distributed lag (NARDL) results for Lithuania.

Variable	Coefficient	*p*-Value
Constant	7568.96	0.0001
GHG (−1)	−1.9087	0.0001
GVA^+ (−1)	0.7277	0.0002
GVA^- (−1)	1.0022	0.0003
ΔGHG (−1)	0.5885	0.0079
ΔGHG (−2)	0.3294	0.0360
ΔGVA (0)	0.2239	0.0009
ΔGVA (−1)	−0.4746	0.0014
ΔGVA (−2)	−0.2048	0.0213
S_2004	63.0262	0.2218
D_2009	15.8409	0.7669

Additional hypotheses:	*Additional estimations, p-values:*
h_1: $\rho = \theta^+ = \theta^- = 0$ reject, p-value 0.0009	Normality of residual: 0.0025
h_2: $\omega_0 = \omega_1 = \omega_2 = 0$ reject, p-value 0.0003	Unit-root of residual (constant): <0.0001
h_3: $\omega_0 = \omega_1 = \omega_2 = \alpha_1 = \alpha_2 = 0$ reject, p-value 0.0005	Unit-root of residual (trend): 0.0007
Long-run coefficients:	ARCH effect: 0.9904
$L^+ = 0.3813$, p-value: 0.7510	R-squared: 0.9370
$L^- = 0.5251$, p-value: 0.8256	

Source: authors' calculations based on Eurostat [9,70] data, 2022.

Hypotheses h_2 and h_3 are rejected as well, indicating that there are short-run relationships between GHG and GVA. Therefore, the GHG and GVA correlations in Lithuania are strong and can be explained by equilibrium relationships. However, dummy variables have no statistically significant effect.

The null hypothesis of normal distribution is rejected, showing that the residuals are not normally distributed. The unit-root hypothesis is rejected, showing that residuals are stationary with both trend and constant only. In addition, there are no statistically significant ARCH effects.

The coefficient of determination indicates the model's strong explanatory power ($R^2 > 0.7$).

After sequentially omitting insignificant variables (see Appendix B), the abbreviated model shows similar relationships. Because the time dummy variables were omitted, the QLR test was performed, and it shows a statistically structural break in 2011.

When analyzing data for Latvia, there are no statistically significant effects from GHG (−1) as well as GVA (−1) (see Table 5). However, the negative coefficient of GVA (−1) shows that the increase in the gross value-add leads to equilibrium in greenhouse gas emissions. Yet, this relationship is weak and statistically insignificant. Long-term impact hypotheses h_1 and h_4 can be accepted, which means that there are no significant long-term effects between GHG and GVA.

Table 5. Autoregressive distributed lag (ARDL) results for Latvia.

Variable	Coefficient	*p*-Value
Constant	−178.964	0.6636
GHG (−1)	0.2337	0.4852
GVA (−1)	−0.4889	0.3373
ΔGHG (−1)	−0.7100	0.1124
ΔGVA (0)	0.1273	0.4911
ΔGVA (−1)	0.3828	0.1941
ΔGVA (−2)	0.2270	0.2928
S_2004	−14.4963	0.7242
D_2009	−50.2782	0.4358

Additional hypotheses:	*Additional estimations, p-values:*
h_1: $\rho = \theta = 0$ accept, *p*-value 0.4705	Normality of residual: 0.1284
h_2: $\omega_0 = \omega_1 = \omega_2 = 0$ accept, *p*-value 0.3370	Unit-root of residual (constant): <0.0001
h_3: $\omega_0 = \omega_1 = \omega_2 = \alpha_1 = 0$ accept, *p*-value 0.1942	Unit-root of residual (trend): 0.8537
h_4: $\rho = \theta$ accept, *p*-value 0.3868	ARCH effect: 0.8381
	R-squared: 0.4806

Source: authors' calculations based on Eurostat [9,70] data, 2022.

Hypotheses h_2 and h_3 are accepted as well, showing that there are no statistically significant short-run effects, nor does any individual short-run regressor have a statistically significant impact. As a result, there is no evidence for the 'inverse U' shape of the relationship between GHG and GVA when analyzing data for Latvia.

Furthermore, both dummy variables show no statistically significant effect. However, unlike analyzing Lithuanian data, their coefficient values are estimated to be negative.

The normal distribution hypothesis is accepted, indicating that the residuals are normally distributed. The unit-root hypothesis is accepted, indicating that residuals are stationary, but only when using the model with a constant. No residual ARCH effects were discovered either.

The coefficient of determination indicates the model's medium explanatory power ($R^2 > 0.4$).

The condensed model exhibits only a short-run GVA effect that was statistically insignificant in the full model (see Appendix C). The QLR test was run since all dummy variables were omitted, but it did not find a statistically significant break point.

Finally, the estimations for the Estonian NARDL model are calculated (see Table 6). Both GHG (−1) and GVA^+ (−1) have a statistically significant effect with *p*-values less than 0.05. The GHG (−1) effect is negative; thus, this may well indicate equilibrium relationships. However, the long-run impact hypothesis h_1 is accepted, showing that the model does not show the complete long-run relationships for all three parameters. The long-run negative coefficient L^- is smaller than the positive L^+, but both are statistically insignificant.

Hypotheses h_2 and h_3 are rejected, showing that GHG and GVA also have short-run relationships. In other words, the short-term effect is statistically significant, and the lagging values of gross value added can help explain future changes in greenhouse gas emissions. To summarize, there is evidence that gross value-added leads to greenhouse gas emissions in Estonia and that this leads to equilibrium.

Table 6. NARDL results for Estonia.

Variable	Coefficient	*p*-Value
Constant	563.674	0.0618
GHG (−1)	−0.5566	0.0492
GVA^+ (−1)	0.7830	0.0350
GVA^- (−1)	0.3566	0.1025
ΔGHG (−1)	−0.2750	0.2581
ΔGHG (−2)	−0.1921	0.1804
ΔGVA (0)	0.4718	0.0016
ΔGVA (−1)	0.0965	0.5659
ΔGVA (−2)	−0.0173	0.8890
S_2004	63.6336	0.0225
D_2009	73.7197	0.0251

Additional hypotheses:	*Additional estimations*, *p-values:*
h_1: $\rho = \theta^+ = \theta^- = 0$ accept, *p*-value 0.159031	Normality of residual: 0.06679
h_2: $\omega_0 = \omega_1 = \omega_2 = 0$ reject, *p*-value 0.0095	Unit-root of residual (constant): 0.0050
h_3: $\omega_0 = \omega_1 = \omega_2 = \alpha_1 = \alpha_2 = 0$ reject, *p*-value 0.0273	Unit-root of residual (trend): 0.0457
Long-run coefficients:	ARCH effect: 0.9755
$L^+ = 1.4068$, *p*-value: 0.1981	R-squared: 0.7047
$L^- = 0.6407$, *p*-value: 0.4720	

Source: authors' calculations based on Eurostat [9,70] data, 2022.

When analyzing time dummy variables, both the crisis period of 2009 and joining the EU in 2004 show a statistically significant effect. However, they have a positive effect on greenhouse gas emissions. As a result, greater data on carbon emissions may help to broaden this study.

The residuals are normally distributed. The residuals are also stationary when using both unit-root models with a trend and with constant only. There are no statistically significant residual ARCH effects.

The coefficient of determination indicates the model's strong explanatory power ($R^2 > 0.7$).

After sequentially omitting insignificant variables (see Appendix D), the abbreviated model shows similar relationships except that the financial crisis represented by the dummy variable has a negative instead of a positive coefficient.

90To summarize, comparable findings were obtained for all three nations in the sample.

Next, the panel data series (stacked time series) are analyzed and the estimations for all three countries using the ARDL model are calculated (see Table 7). This uses three cross-sectional units observed over 21 periods (years).

Table 7. Panel data (stacked time series) for all three countries' ARDL results.

Variable	Coefficient	*p*-Value
Constant	40.4640	0.1549
GHG (−1)	−0.0006	0.9638
GVA (−1)	−0.0203	0.4979
ΔGHG (−1)	−0.0794	0.4812
ΔGHG (−2)	0.1465	0.1813
ΔGVA (0)	0.2247	<0.0001
S_2004	−11.5443	0.6574
D_2009	−19.3475	0.6023

Additional hypotheses:	*Additional estimations*, *p-values:*
h_1: $\rho = \theta = 0$ accept, *p*-value 0.3523	Normality of residual: 0.2152
h_2: $\omega_1 = 0$ reject, *p*-value < 0.0001	Unit-root of residual (constant): 0.0002
h_3: $\omega = \alpha = 0$ reject, *p*-value 0.0001	Unit-root of residual (trend): 0.0142
h_4: $\rho = \theta$ accept, *p*-value 0.6365	R-squared: 0.3760

Source: authors' calculations based on Eurostat [9,70] data, 2022.

GHG (−1) and GVA (−1) have no statistically significant impact. Both hypotheses h_1 and h_4 for long-run impacts are accepted, suggesting that there are no major long-term consequences.

However, the short-term impact is statistically significant. Hypotheses h_2 and h_3 are rejected, demonstrating that GHG and GVA have short-run correlations. This demonstrates that, after all, the shift in GVA is driving the increase in GHG.

None of the time dummy variables are statistically significant, but their coefficient values are negative.

The null hypothesis for normal distribution is accepted, indicating that the residuals are normally distributed. The unit-root hypothesis is rejected, which shows that residuals are not stationary when using models with both a trend and a constant.

As previously stated, the limitation of panel data analysis is that it excludes ARCH estimations for residual clustering. The coefficient of determination indicates the model's weak explanatory power ($R^2 < 0.4$).

In conclusion, ARDL and NARDL models can be used to look at how greenhouse gas (GHG) emission equivalent and gross value added (GVA) in agriculture in different states are related to each other. On the other hand, the traditional ARDL model was selected for Latvia and panel data since no statistically significant asymmetric effects were found. Most time series are stationary and cointegrated with a p-value less than 0.05. In almost every instance, the residuals are distributed normally, with no substantial ARCH effects discovered. The effects are most clear and evidence for equilibrium relationships can be observed when looking at data from Lithuania and Estonia. They are least clear when looking at data from Latvia.

4. Discussion

4.1. Contextualization with Previous Research

The findings of the ARDL modeling provide a diversity of perspectives on the current scientific dispute. Other nations that have been employed in comparable studies on greenhouse gas emissions using the ARDL technique are mostly Asian countries [73–76]. However, it has been used in other studies on more developed economies, such as the United States [77], Japan [78], South Africa [79], Saudi Arabia [80], and Singapore [81]. Some authors conducted research on several nations at the same time [82]. Nevertheless, there are some studies that look at greenhouse gas emissions in Lithuania and neighboring Baltic countries [12,83,84].

Although similar methodologies have been utilized in the work of other researchers, the most recent data from the Baltic States have been investigated in this paper. This not only led to the discovery of structural break points, but also better established the nature of dependencies between greenhouse gas emissions (GHG) and gross value added produced in agriculture (GVA). The study's primary findings may be classified into the following categories:

In almost all circumstances, GVA has an impact on GHG. On the one hand, the short-term impacts of GVA on GHG change mostly reflect this effect. An exception was discovered in the study of Latvia data; however, when all three nations' data are merged, GVA has a statistically significant influence on GHG in the short run. GHG and GVAs fluctuated in all three nations but grew over the study period. Thus, undoubtedly, GVA significantly influences GHG, as has been observed in other authors' analyses. However, value added is only used by a few researchers to analyze economic growth [12,84]. Other writers incorporated data such as energy use and actual GDP [75]. Other writers have also utilized panel data time series [85].

Analyzing Lithuanian data revealed the effect between GVA and GHG, which stabilizes and achieves equilibrium in the long run. A similar impact was discovered in the examination of Estonian data that GHG stabilizes as it increases, but the changes in GVA do not allow for a statistically significant explanation of the inverted 'U-shaped' form. It is worth noting that such an influence was not discovered in the data analysis for all nations in other researchers' studies [59]. Other authors' studies that included the examination of similar variables and employed longer research periods found that the impacts were also varied when assessing data from other nations. The study's findings, on the other hand, indicated that there is inadequate evidence supporting the inverted 'U-shaped' effect of the environmental Kuznets curve (ECK) [17]. The effects of GVA on GHGs approach equilibrium but do not reverse. Typically, authors are proponents of the U-shaped hypothesis. The inverted U theory was, however, dismissed in some cases [86]. For example, empirical evidence shows that the inverted U-shaped hypothesis is not true in Qatar when CO_2 emissions are used, but it is true when the ecological footprint is used [87].

The relationships between greenhouse gas emissions (GHG) and gross value added produced in agriculture (GVA) have undergone significant structural modifications. Time dummy variables depicting nations' entry into the EU in 2004 and the era of economic crisis in 2009 are used in this research. In some instances, these variables are statistically significant. Statistically significant breakpoints were detected by evaluating data from Estonia. This demonstrates that the crisis of 2009 as well as joining the EU had an impact on greenhouse gas emissions. In other words, this may indicate a more efficient use of agricultural resources. Dummy variables are statistically insignificant when analyzing non-panel data for Lithuania and Latvia. However, the QLR test for Lithuania showed a significant breakpoint in 2011. Other researchers have looked at structural breaks through dummy variables and discovered them, particularly when utilizing long-term data. These structural breaks happen at important economic events in that country [60,87,88].

4.2. Future Research Guidelines

The key constraint of the research is that the data utilized in the study date back to 1998, since only such statistics on Lithuanian gas emissions and agricultural value added are available. Other research has utilized longer-term data, such as since the 1970s, which has given them greater flexibility in choosing econometric models and modeling these correlations. The investigation also failed to discover asymmetric links in all countries, rejecting both long-term and short-term asymmetry hypotheses when analyzing data for Latvia or panel data. Hence, the conventional ARDL model was selected more often for relationship assessment rather than the more sophisticated NARDL model often used by other researchers [62]. As with other research, as asymmetric connections are revealed, the NARDL model method is used [89]. Furthermore, both short-term and long-term impacts have been reported by other authors [90].

On the other hand, the research might be expanded, particularly if data from more recent times become accessible. Time dummy variables, such as those for the pandemic period 2020–2021, may therefore be used. Furthermore, it is necessary to better understand and analyze the shifting link between greenhouse gas emissions and the gross value added caused by the significant increase in agricultural energy costs. More dummy variables may be used if they are linked more closely to the breakpoints identified in ARDL models, assuming choosing separate breakpoints for each state. The study's findings may be compared to those of other nations by incorporating and categorizing countries into various areas, such as Eastern European and Western European countries. Another key consideration is that when more data are studied, more variables may be eliminated from the model. If this study had more observations, it could more efficiently remove less significant variables to improve the explanatory power of this model.

To evaluate the inverse 'U' relationships, additional explanatory factors can be utilized instead of or in addition to economic growth. These include variables representing economic policy uncertainty [77], inward foreign direct investment [76], or even more alternative approaches such as variables representing renewable energy [91], ecological footprint [92], and urbanization [78,80,81]. According to multiple studies, a key finding is that trade openness has a statistically negligible association with carbon emissions [79,93].

Other authors used a different technique to look at these linkages. More advanced ARDL techniques—such as the dynamic autoregressive distribution lag (DARDL) [92] and quantile autoregressive distribution lag (QARDL) models [94]—are included. Others used the ARDL cumulative sum (CUSUM) Test [95] or a combination of VECM and ARDL methods [60]. Other researchers also use the Granger causality test [96]. The findings show that there is a short- and long-term link between agricultural productivity, economic development, and carbon dioxide emissions in the countries studied. Other writers claim that linear logarithm models are more efficient than basic linear models [97,98]. Recent studies look at the link between fossil fuel and renewable energy use, pollution, and economic growth in both panel and time series settings.

4.3. Practical Implications

The three Baltic nations studied—Lithuania, Latvia, and Estonia—were selected for their comparable agricultural structures, natural circumstances, and application of the Common Agricultural Policy. The general agricultural policy of 2023–2027—not only in the Baltic countries, but also in all EU countries—will be more oriented towards the sustainable solution of environmental problems, which is likely to reduce greenhouse gas emissions and contribute to the implementation of the goals of the Green Deal and net-zero commitments. The results of our research also showed that, with the exception of Lithuania, there were no 'U'-shaped relationships between economic growth and greenhouse gas emissions. This shows that economic growth alone is not enough to fix environmental problems. The findings imply that the government should prioritize carbon-reduction measures and policies. Other researchers argue that expanding the trade sector is important because of the role it plays in lowering environmental deterioration in the nation, which improves environmental quality directly [96]. For example, policy implications might suggest that increased trade between the nations be allowed [93]. One conclusion is that any environmental policy aimed at reducing nonrenewable energy usage and carbon dioxide emissions would necessarily lead to more renewable energy consumption, which would improve trade openness and, in turn, speed up economic development [98]. This is particularly crucial in the Baltic states, where renewable energy sources are not widely used. Other authors emphasize renewable energy sources [99,100] as a way to minimize greenhouse gas emissions while maintaining economic development.

5. Conclusions

This research investigates the link between greenhouse gas equivalent and the gross value added in agriculture. This is explained by the fact that numerous worldwide linkages between agriculture and climate change have been uncovered and validated. This work not only adds to the main body of knowledge, but it also expands it to countries less analyzed by others. From 1998 through to 2019, the research examines data from Lithuania, Latvia, and Estonia together and individually. Since the agricultural systems and environmental circumstances in all three nations are similar, the research findings are comparable and provide new insights. The NARDL and ARDL models were used to find and further assess the connections and their forms between the variables that were chosen. This study covers nonlinear relationship analysis and asymmetric relationship analysis to test if there is a convex curve between variables and changes in its structure.

The study led to three main conclusions. First, agriculture's gross value added has a statistically significant positive influence on greenhouse gas emission equivalent. Such impacts have been discovered in almost all situations or via the study of aggregate national statistics. This is consistent with the findings of other authors' research, and the gross value added greatly boosts greenhouse gas emissions. Second, by examining Lithuania and Estonia data, the influence that stabilizes and achieves equilibrium in the long run was identified. An examination of Estonian data indicated similar results, but without the asymmetric influence of gross value added on greenhouse gas emissions equivalent. Therefore, Lithuania's data show the most evidence of the inverse 'U' environmental Kuznets curve relationship between economic performance and greenhouse gas equivalent. Finally, major structural alterations have been observed between these dependencies. It was discovered that there were modifications in relationships from 2004 and 2009 for Estonia. The nation's greenhouse gas emissions have been affected because of its EU entry and accompanying reforms, as well as the 2009 financial crisis, a period of diminishing production and GDP.

The data used in the analysis goes back to 1998, since only that much data on the Baltic States' gas emissions and agricultural value-added figures are available. Other studies used longer-term data, such as from the 1970s, allowing them more flexibility in selecting econometric models and modeling relationships. Asymmetry hypotheses for long-term and short-term relationships were often rejected, hence the traditional ARDL approach was chosen more often for underlying relationship evaluation rather than the more advanced NARDL model. However, if more current data become available, the study can be expanded. More time-bound dummy variables, such as pandemic 2020–2021, may be employed. The huge rise in agricultural products and energy prices may have also shifted the connection between greenhouse gas emissions and gross value added. More dummy variables may be utilized that are tied to ARDL breakpoints. Therefore, individual breakpoints can be chosen for each state. The study's results may be compared to other countries by classifying them as Eastern or Western European. Furthermore, when more data are reviewed, more factors may be added to the model. Future research may examine—in panel and separate time series settings—the relationship between the usage of fossil fuels and renewable energy, pollution, and economic development, on which factors (i.e., the percentage of fossil fuels used, trade openess) may have an impact on the curve shape between economic performance and greenhouse gas emissions in the Baltic countries.

The results of the study have important policy implications.

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Appendix A

Table A1. Information criteria for best time lag selection.

Information Criteria	**Schwarz Criterion**			**Akaike Criterion**			**Hannan-QUINN Criterion**		
Time Lag	**q = 1**	**q = 2**	**q = 3**	**q = 1**	**q = 2**	**q = 3**	**q = 1**	**q = 2**	**q = 3**
				Lithuania					
$p = 1$	238.1	233.4	228.3	231.1	224.4	217.9	232.5	226.2	219.6
$p = 2$	225.7	213.4	209.3	218.1	204.0	198.0	219.4	205.6	199.9
				Latvia					
$p = 1$	226.2	229.0	215.6	219.2	220.0	205.3	220.6	221.8	207.0
$p = 2$	219.0	221.1	217.9	211.4	211.6	206.5	212.7	213.2	208.5

Table A1. *Cont.*

Information Criteria	Schwarz Criterion			Akaike Criterion			Hannan-QUINN Criterion		
Time Lag	**q = 1**	**q = 2**	**q = 3**	**q = 1**	**q = 2**	**q = 3**	**q = 1**	**q = 2**	**q = 3**
				Estonia					
$p = 1$	207.6	213.4	194.9	200.7	204.5	184.5	202.0	206.2	186.3
$p = 2$	201.3	207.2	195.5	193.7	197.7	184.1	195.0	199.3	186.1
				Panel					
$p = 1$	686.4	694.5	652.9	671.8	675.7	630.5	677.5	683.0	639.2
$p = 2$	648.4	654.5	656.7	632.1	634.1	632.2	638.4	642.0	641.7

Source: authors' calculations based on Eurostat [9,70] data, 2022.

Appendix B

Table A2. NARDL results for Lithuania after sequentially omitting insignificant variables.

Variable	Coefficient	*p*-Value
Constant	7007.23	<0.0001
GHG (−1)	−1.7567	<0.0001
GVA^+ (−1)	0.6828	<0.0001
GVA^- (−1)	0.9376	0.0001
ΔGHG (−1)	0.5356	0.0048
ΔGHG (−2)	0.4279	0.0022
ΔGVA (0)	0.2385	0.0002
ΔGVA (−1)	−0.4303	0.0010
ΔGVA (−2)	−0.1924	0.0192

Additional hypotheses:
h_1: $\rho = \theta^+ = \theta^- = 0$ reject, *p*-value 0.0002
h_2: $\omega_0 = \omega_1 = \omega_2 = 0$ reject, *p*-value < 0.0001
h_3: $\omega_0 = \omega_1 = \omega_2 = \alpha_1 = \alpha_2 = 0$ reject, *p*-value < 0.0001
Long-run coefficients:
$L^+ = 0.3887$, *p*-value: 0.8390
$L^- = 0.5337$, *p*-value: 0.7414

Additional estimations, *p-values:*
Normality of residual: 0.0016
Unit-root of residual (constant): 0.1893
Unit-root of residual (trend): 0.6138
ARCH effect: 0.9308
R-squared: 0.9224
QLR test *p*-value: 0.0216, year: 2011

Source: authors' calculations based on Eurostat [9,70] data, 2022.

Appendix C

Table A3. ARDL results for Latvia after sequentially omitting insignificant variables.

Variable	Coefficient	*p*-Value
Constant	21.29	0.0875
ΔGVA (0)	0.2275	0.0300

Additional estimations, *p-values:*
Normality of residual: 0.7553
Unit-root of residual (constant): 0.0110
Unit-root of residual (trend): 0.6849
ARCH effect: 0.6540
R-squared: 0.2480
QLR test *p*-value: 0.1716, year: 2002

Source: authors' calculations based on Eurostat [9,70] data, 2022.

Appendix D

Table A4. NARDL results for Estonia after sequentially omitting insignificant variables.

Variable	Coefficient	*p*-Value
Constant	789.94	0.0016
GHG (−1)	−0.7515	0.0015
GVA^+ (−1)	0.9025	0.0016
GVA^- (−1)	0.3309	0.0166
ΔGVA (0)	0.4034	0.0005
S_2004	44.0169	0.0229
D_2009	−77.2390	0.0110

Additional hypotheses: h_1: $\rho = \theta^+ = \theta^- = 0$ reject, *p*-value 0.0082 *Long-run coefficients:* $L^+ = 1.2009$, *p*-value: 0.2127 $L^- = 0.4403$, *p*-value: 0.4303	*Additional estimations, p-values:* Normality of residual: 0.3051 Unit-root of residual (constant): 0.0110 Unit-root of residual (trend): 0.6849 ARCH effect: 0.1004 R-squared: 0.8174

Source: authors' calculations based on Eurostat [9,70] data, 2022.

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