agriculture

Article

Evaluating Enteric Fermentation-Driven Environmental Kuznets Curve Dynamics: A Bayesian Vector Autoregression Comparative Study of the EU and Least Developed Countries

Eleni Zafeiriou [1], Spyros Galatsidas [2,*], Christina Moulogianni [3], Spyridon Sofios [4] and Garyfallos Arabatzis [2]

1 School of Agricultural Development, Faculty of Agricultural and Forestry Sciences, Democritus University of Thrace, 68200 Orestiada, Greece; ezafeir@agro.duth.gr
2 School of Forestry and Management of the Environment and Natural Resources, Faculty of Agricultural and Forestry Sciences, Democritus University of Thrace, 68200 Orestiada, Greece; garamp@fmenr.duth.gr
3 Department of Agricultural Economics, Aristotle University of Thessaloniki, 54124 Thessaloniki, Greece; kristin@agro.auth.gr
4 Independent Authority for Public Revenue, 54110 Thessaloniki, Greece; spyrossofios@gmail.com
* Correspondence: sgalatsi@fmenr.duth.gr

Abstract: Global warming and climate change, primarily driven by human activities, with agriculture playing a significant role, have become central topics of scientific research. Livestock production, especially enteric fermentation, is a major source of greenhouse gas emissions, making it a focal point for both climate change adaptation and mitigation strategies. Both the European Union (EU) and Least Developed Countries (LDCs) are highly dependent on agriculture, particularly livestock, which plays a key role in their economic growth. In developing countries, livestock systems are evolving rapidly due to various factors, while in the EU, the livestock sector remains economically and socially significant, representing 36% of total agricultural activity. This study explores the environmental impact of enteric fermentation in livestock production, alongside the economic value it generates in both the EU and LDCs. The analysis utilizes a Bayesian Vector Autoregression (BVAR) methodology, which provides a more robust performance compared to traditional models like Vector Autoregression (VAR) and the Vector-error Correction Model (VECM). This research identifies significant relationships between the variables studied, with structural breaks quantified to reflect the impact of initiatives undertaken in both regions. Interestingly, the results challenge the environmental Kuznets curve, which hypothesizes an inverted U-shaped relationship between economic growth and environmental degradation, as proposed by Stern. This suggests that stronger economic incentives may be necessary to enhance policy effectiveness and promote eco-efficiency. The distinctive characteristics of livestock production in the EU and LDCs should be carefully considered when shaping agricultural policies, with a strong emphasis on farmer education as a critical factor for success. Additionally, corporate management practices must be tailored to address the unique needs, strengths, and challenges of livestock businesses in these two diverse regions.

Keywords: enteric fermentation; Kuznets; livestock; the European Union (EU); least developed countries (LDCs); Bayesian vector autoregression models (BVAR models)

check for updates

Citation: Zafeiriou, E.; Galatsidas, S.; Moulogianni, C.; Sofios, S.; Arabatzis, G. Evaluating Enteric Fermentation-Driven Environmental Kuznets Curve Dynamics: A Bayesian Vector Autoregression Comparative Study of the EU and Least Developed Countries. *Agriculture* **2024**, *14*, 2036. https://doi.org/10.3390/agriculture14112036

Received: 3 September 2024
Revised: 28 October 2024
Accepted: 8 November 2024
Published: 12 November 2024

1. Introduction

Climate change is driven by various sectors, with fossil fuels and agriculture being among the most significant contributors. As of 2020, the energy sector accounted for approximately 34.3 gigatons (Gt) of carbon dioxide equivalent (CO_2e), accounting for about 73.2% of total global greenhouse gas (GHG) emissions. In the same year, agriculture, forestry, and other land uses (AFOLU) contributed around 11.2 Gt CO_2e, or roughly 18.4% of global emissions [1–9]. Industrial processes such as cement, chemical, and metal production contributed an additional 3.3 Gt CO_2e, accounting for 5.3% of global emissions [5].

Globally, agricultural emissions—especially from livestock—are particularly significant. Livestock emissions stood at 7.1 Gt CO_2e in 2005, which was about 14.5% of human-induced emissions. This figure has since risen to around 8.1 Gt CO_2e (FAO), with a substantial portion coming from enteric fermentation in ruminants. Livestock-related emissions also stem from manure management and feed production. Enteric fermentation is a natural part of ruminants' digestive processes, producing methane (CH_4) as a by-product [6–10]. Methane production from cattle, the primary emitters, varies with factors like animal species, age, feeding practices, and environmental conditions. Studies show that CH_4 emissions increase as younger cattle mature and tend to decrease in adults aged 4 to 10 years, with higher emissions associated with poor feed quality and high temperatures [11–14].

In the European Union (EU), greenhouse gas (GHG) emissions from agriculture in 2022 accounted for approximately 11–12% of total emissions, a share that has remained fairly consistent in recent years. Other sectors such as energy production, industry, and transport contributed more significantly, with energy and manufacturing combined representing the largest portions, particularly due to their reliance on fossil fuels. The energy sector alone accounted for over 75% of total emissions in some estimates, largely driven by power generation, while transport and industry also had significant shares (around 20–25% and 21%, respectively) [11–15]. In 2018, enteric fermentation alone represented around 45% of agricultural GHG emissions within the EU, primarily from ruminants. When feed production and processing are included, livestock emissions contribute 81–86% of the sector's total emissions [6,9]. By 2019, manure management within the EU had generated approximately 234 kilotons of N_2O, which, due to its high global warming potential, accounts for around 70 million tons of CO_2e. Additionally, indirect CO_2 emissions from energy used in manure handling and application add approximately 35 million tons annually, alongside 3.8 million tons of NH_3 released from manure practices [10–17].

For many Least Developed Countries (LDCs), agriculture, particularly livestock, remains crucial to rural economies. These countries face unique challenges, such as low-fertility soils and high rates of poverty, which can hinder the transition to sustainable agricultural practices. Low agricultural productivity, coupled with land degradation, erosion, and water scarcity, exacerbates food insecurity and hampers sustainable development. Government support for farmers is limited, and agriculture's contribution to both employment and economic growth remains comparatively low in many African nations. Understanding the environmental impact of agriculture in these regions requires quantifying GHG emissions from enteric fermentation, the most significant agricultural contributor to emissions in LDCs [12,17]. Though LDC policies typically focus on enhancing resilience, improving productivity, and promoting low-cost, sustainable practices. More specifically, agroecological practices such as rotational grazing, improved forage crops, and integrated livestock–crop systems can enhance feed quality, reduce methane emissions, and improve soil health [18], enhanced livestock health programs aiming to reduce methane emissions by improving animal productivity and health. The particular programs involve selection of animals with higher feed efficiency and lower methane output, enabling smaller, healthier herds that require fewer resources and emit less methane [19]. Another measure involves funded training programs aiming to promote methane-reducing techniques such as improved feed, better pasture management, and community-based livestock management, which improve livestock productivity while minimizing environmental impacts, and, finally, funding and collaboration programs that support methane reduction through agroforestry, improved pasture management, and low-cost technologies suited to local conditions [18–23].

Achieving climate neutrality by 2030 is a priority for the EU, with mitigation strategies focused on the agricultural sector as part of the non-emissions trading system (non-ETS) [18–22]. However, the importance of livestock to economic growth means emissions reduction remains a secondary goal in LDCs compared to food security and poverty alleviation. Conversely, in the EU, where environmental sustainability is a primary focus, the agriculture sector is central to achieving climate goals. By applying the environmental Kuznets curve (EKC) framework, which explores the link between economic growth and environmental degradation, policymakers can balance the dual aims of economic and environmental health. For instance, methane emissions could potentially be reduced by 50% within the next decade through targeted measures, which may slow warming by around 30% [22–28].

To address livestock-related emissions, the EU has adopted practices guided by circular economy principles and precision farming. Optimizing water and fertilizer use in feed production for livestock and improving air quality during animal feeding are strategies that help to reduce emissions while lowering production costs, thus fostering sustainable development [28–31]. The methane strategy adopted in 2020 involves reducing emissions from enteric fermentation through improved livestock management practices, dietary adjustments, and promoting innovative technologies such as feed additives that can inhibit methane production in ruminants [31]. In addition, the CAP eco-schemes are offering financial incentives for farmers who adopt climate-friendly practices, including precision livestock feeding, rotational grazing, manure management, and, last but not least, investments in research on feed additives, such as 3-NOP (3-nitrooxypropanol) and seaweed-based solutions, used to mitigate methane emissions from enteric fermentation by up to 30%.

However, successful implementation of such practices depends on farmers' willingness to adopt them. Farmers may be hesitant due to short-term income losses or perceived risks, particularly if the changes require significant labor adjustments. Novel practices often appear risky if they demand increased labor or costs, making cost-effectiveness crucial to achieving wide adoption [27–31].

In addition to these specific agricultural strategies, broader economic considerations affect the climate policies in place. The global economic crisis of 2007, followed by the coronavirus pandemic, prompted governments to adopt Keynesian economic policies to stabilize economies. In this context, green Keynesianism, which integrates both economic and environmental policy goals, offers a model to simultaneously address economic recovery and ecological sustainability. These policies serve as a corrective mechanism to not only protect against economic downturns but also to mitigate ecological threats [28–32].

Keeping the above in mind, the present work makes an effort to detect and quantify the economic–environmental performance association for the agricultural activity of livestock for two regional entities with different objectives, namely EU and LDCs. More specifically, the first group of EU countries involves self-sufficient agricultural entity in terms of production with a policy characterized by a strong economic dimension but focusing mainly on zero carbon agricultural sector. On the other hand, LDCs are primarily agricultural with food insecurity and poverty being the main traits with policy measures focus mainly on poverty alleviation and food security. As a proxy for environmental performance, we employ a carbon dioxide emission equivalent generated by enteric fermentation, while the value added generated by agriculture was employed as a proxy for economic performance in agriculture. The estimation methodology employed is the Bayesian VAR, namely the BVAR methodology, since it provides less robust results for the limited time period studied [21–24].

The contribution and novelty of this work are multi-faceted. Firstly, it delves into the relatively underexplored area of enteric fermentation emissions within agriculture, a sector often overlooked in environmental Kuznets curve (EKC) analyses, despite the EKC framework's widespread application across other industries. Secondly, this study fills a critical gap in the literature by providing fresh insights into how livestock management practices impact environmental sustainability, particularly through methane emissions. Thirdly, it offers a unique comparative analysis of EKC dynamics related to enteric fer-mentation emissions in the European Union (EU) versus Least Developed Countries (LDCs). This comparative approach allows for a nuanced understanding of how varied economic and policy contexts shape the relationship between livestock emissions and environmental degradation. Finally, by contextualizing enteric fermentation within the EKC framework, this study equips stakeholders with data-driven insights to develop targeted, locally informed interventions that support sustainable agricultural practices while balancing economic and environmental goals [33–39].

This paper is organized as follows: Section 2 provides the data and the methodology employed, Section 3 analyzes and discusses the results, and Section 4 concludes.

2. Materials and Methods

The statistical model to be estimated aims to capture the interlinkages of the environmental–economic performance that can be described by the following function:

$$f(EMIti, VAA_i, VAA_i^2) \quad (1)$$

where i denotes either the LDCs group or the EU group, the EMI denotes the carbon dioxide emissions equivalent generated by enteric fermentation in carbon emissions equivalent per 1000 hectares of land, VAA_i, and VAA_i^2 denotes the value added by agriculture per capita of the rural population. The VAA is measured in US dollars. All the variables are in logarithmic form. This particular model aims to unveil the agricultural income environmental degradation generated by enteric fermentation interlinkages. The findings may validate or reject the existence of association and provide the pattern of the relationship among the variables studied for two different groups of countries, namely the EU and the LDCs. The sector of agriculture in LDCs is the dominant sector, since 70% of the total population is occupied in this sector. The greatest problem confronted in those areas involves poverty and food insecurity, a significant feature of rural areas. Therefore, poverty alleviation and food security are high-priority issues to be addressed in these areas [31]. In addition, agriculture is also an important sector of the European economy [23]. More specifically, livestock products dominate agricultural production in both research areas. Actually, livestock production, including meat, dairy, and eggs, represents nearly 40% of the EU's total agricultural value, while, for LCDs, livestock contributes significantly to rural livelihoods, providing a source of income, nutrition, and employment in areas where crop production may be limited due to low soil fertility or water scarcity [18,19].

The abundance of studies on environmental–economic performance interlinkages involves many different research areas, different methodologies, and conflicting results. Widely used methodologies employed in the study of the specific issue are linear and nonlinear cointegration techniques for time series and panel data, fuzzy modeling, Vector Autoregression (VAR), and Bayesian Vector Autoregression (BVAR) analysis [33–41].

Carbon emissions from specific agricultural activities, such as enteric fermentation, present varied challenges across regions with contrasting environmental policies. In the European Union (EU), the primary goal is to achieve zero-carbon agriculture, aligning with stringent climate targets and policies that prioritize sustainability. In contrast, in Least Developed Countries (LDCs), the focus remains on increasing agricultural productivity and economic returns, with climate concerns often being secondary to food security and income generation. However, a few obstacles hinder effective methane (CH_4) reduction strategies, even within the EU. Key challenges include the absence of binding reduction targets for CH_4 at the farm level, limited enforcement of mandatory CH_4 mitigation actions, and a lack of alignment between climate objectives and current air quality standards. As a result, the European Commission's CH_4 Strategy risks being less impactful than anticipated, falling short of its emission reduction goals. Addressing these gaps, such as implementing farm-level targets and synchronizing CH_4 strategies with broader climate goals, is crucial for the EU to make substantial progress in agricultural emissions reduction. Meanwhile, for LDCs, the primary barriers to CH_4 reduction in agriculture include limited access to resources, technology, and financial support. As these countries prioritize productivity over emissions reduction, the incorporation of climate resilience practices that also enhance productivity could offer a pragmatic path forward [42].

The data used for the LDCs (Appendix A) and EU-27 (Appendix A) are annual, with the reference periods of 1991–2019 and 1995–2019, respectively, and were derived by FAOSTAT. The EU-27 involves all the members in the EU, except the United Kingdom, since 2020 was the year of BREXIT. On the other hand, the group of the LDCs are characterized by extreme poverty and structural weaknesses often combined with geographical disadvantages. Limitation in human and natural capital makes them vulnerable to health, economic crises, or even natural disasters. Poverty, social inequality, and a poorly developed agricultural sector characterize those groups of countries. In other words, the main objective of the policy implemented should be to address the aforementioned diverse and complex problems in the sector of agriculture and to ensure sustainable access to food. In addition to these particular problems, new challenges related to food price volatility and climate change worsen the policymakers' work even more.

Regarding the model structure, two variables are employed, namely carbon emissions generated by enteric fermentation per 1000 hectares of land and the value added per capita for the rural population as a proxy for agricultural income and the square of agricultural income. All the variables are in logarithmic form and measured in thousands of dollars in order to be comparable. The evolution of the variables for the period studied is illustrated in Figure 1, as follows.

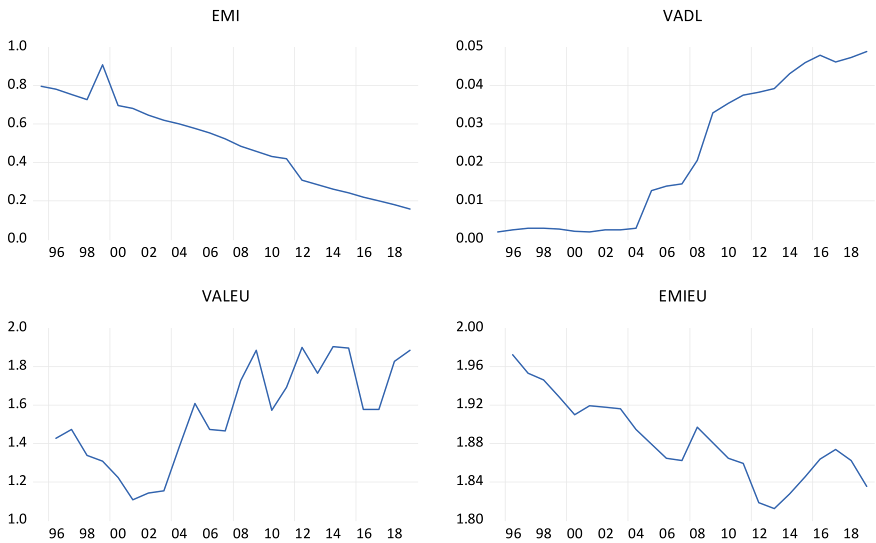


Figure 1. The evolution of the model variables for the time period studied. EMIL denotes CO_2e for LDCS. EMIEU denotes CO_2e for EU. VAL denoted value added by agriculture for LDCS. VADL2 denoted the square value added by agriculture for LDCS. VAEU denoted value added by agriculture. VAEU2 denoted value added by agriculture.

Evidently, the emissions for the case of LDCs are characterized by a declining trend, while, at the same time, an increasing trend is evident for the agricultural income, especially after the year 2003. The figure is indicative of nonstationarity a result that can be validated with the assistance of more econometric tests employed. The next paragraphs aim to provide a concise and precise description of the experimental results, their interpretation, as well as the conclusions that can be drawn. As far as the EU is concerned, in the previous figure, the carbon dioxide emissions equivalent is characterized by a gradually declining trend, while, for the case of value added per capita, the evolution is oscillating, with an evident sharp decrease for the last two years of the period studied.

The graphical illustration provides an indication of the evolution of the variables, while with the assistance of statistic tests, namely unit root tests, and, more specifically, breakpoint unit root tests, we will test the stationarity of the model variables [42].

The next step in our analysis involves the implementation of the BVAR methodology. The specific results allow us to use the Bayesian VAR since the 25 years used as a reference period suggest that the particular methodology outperforms the classical VAR model. The mathematical form of those is the same, though the parameters' estimation and interpretation is totally different. More specifically, the BVAR models, by incorporating prior information about model parameters, secure reliable results, since the particular process stabilizes parameter estimation. The BVAR model estimation was based on the Minnesota prior specification, while all the information is incorporated in the parameters' estimations. Based on the maximum likelihood function, we estimate the posteriors [43–45].

Based on BVAR estimation model, we generate a tractable posterior density function, which is similar to the one of the prior [44]. The prior selected Litterman/Minnesota algorithm for the target parameter is a priori normal, while the zero value of the hyperparameter determines the value of the prior μ, the covariance prior is non-zero, and the matrix of error terms, given that the variance–covariance matrix is diagonal, means that all coefficients are equal to zero. The next step in our BVAR analysis involves the specification of the prior covariance or the target parameter, having incorporated a set of hyperparameters [40]. The value of the hyperparameter λ1 is small since the prior information is more efficient than the sample information. As for the rest of the parameters, λ2 is the regulator of the lag significance of the other variables, while parameter λ3 reflects the impact of the exogenous variable on the endogenous variable. Last but not least, λ4 provides the data scale and variability differences, with the lag decay either linear if λ4 = 1, harmonic, or geometric in case λ4 > 0 [43–45].

The last step in our analysis involves the impulse response function estimation (IRF) for each variable as well as the Forecast Error Variance Decomposition analysis (FEVD). The impulse response analysis is a significant tool in econometric analysis, since it may well describe the evolution of the estimated VAR model's variables as a response to a shock in one or more variables. In other words, this step allows the analyst to trace the transmission of a single shock within the noisy system of equations and, therefore, we can make an assessment of the economic policy impacts in the model variables' evolution within a period that may be 10 or 20 years in cases where the data employed are annual [43–45]. In a similar vein, Variance Decomposition or, in other words, Forecast Error Variance Decomposition is a specific tool that may interpret adequately and, in a narrow way, the relations between variables described by the model estimated. This methodology will amplify the impulse response analysis since it further quantifies the contribution rates of all variables to the impact on the dependent variable [46–48].

The model evaluation was based on the forecast accuracy performance for the classic VAR and BVAR specifications, respectively, with the assistance of the following indices, namely the root mean square error (*RMSE*) and the Mean Absolute Error (*MAE*). Their calculation was based on the following formula:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \overline{y})^2}{n}} \tag{2}$$

$$MAE = \frac{\sum_{i=1}^{n}|y_i - \overline{y}|}{n} \tag{3}$$

The forecast accuracy measures were selected on the basis of sensitivity extending to the deviations from the true values.

The results of the methodology presented above are provided in the Results section.

3. Results

3.1. Descriptive Statistics

Prior to the time series analysis and the BVAR model estimation, we calculated the main descriptive statistics of the model variables. Evidently, the smallest value for variability is met for the value added per capita in LDCs, while, according to the Jarque–Bera values, the null hypothesis of residual normality is rejected for all variables employed. This result verifies the BVAR selection for the data employed in the present analysis. The results are provided in Table 1.

Table 1. Descriptive statistics of the model variables.

Variables	EMIL	EMIEU	VAL	VALEU
Mean	0.486089	1.883134	0.022687	1.552735
Minimum	0.501209	1.876174	0.017425	1.573746
Maxiimum	0.906165	1.971992	0.048747	1.903699
Std. Dev	0.156382	1.811860	0.001819	1.106403
Skewness	0.217959	0.042733	0.019045	0.260658
Kurtosis	0.031668	0.272423	0.121958	−0.156242
Jarque–Bera	1.876353	2.331038	1.285271	1.861752

EMIL denotes CO_2e for LDCS. EMIEU denotes CO_2e for EU. VAL denoted value added by agriculture for LDCS. VAEU denoted value added by agriculture.

3.2. Break Unit Root Tests

Having calculated the main features of the variables employed for the two models, the next step in our analysis involves the breakpoint unit root test application (the Augmented Dickey–Fuller test). Our findings for each variable estimation results are illustrated next in Table 2.

Table 2. ADF break unit root results.

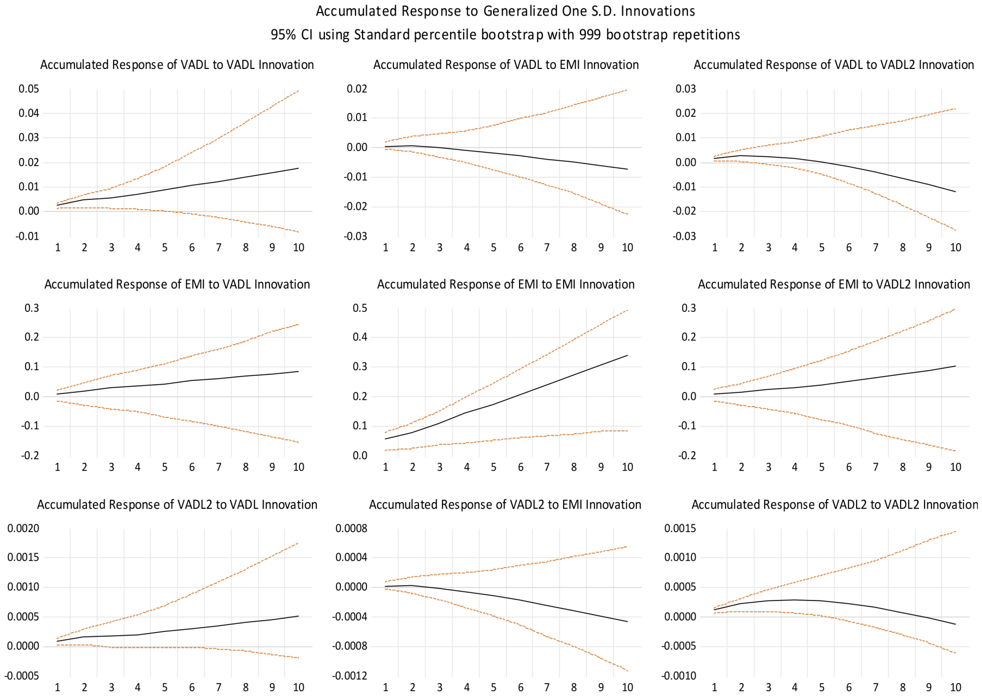
Variables	ADF Break Unit Root	Break Date
EMIL	−2.31 (0.94)	1999
ΔEMIL	−15.0 *** (0.000)	1999
VAL	−3.8 (0.4)	2004
ΔVAL	−5.58 *** (0.0)	2009
EMIEU	−3.46 (0.4)	2008
ΔEMIEU	−5.61 *** (0.00)	2013
VAEU	−4.15 (0.10)	2007
ΔVAEU	−6.35 *** (0.00)	2004

*** reject of unit root test for 1% level of significance with critical values −4.94, −4.44, −4.19 for 1, 5, 10% level of significance EMIL denotes CO_2e for LDCS, EMIEU denotes CO_2e for EU, VAL denotes value added by agriculture for LDCS, VAEU denotes value added by agriculture, ΔEMIL ΔVAL ΔEMIEU ΔVAEU denotes the first differences.

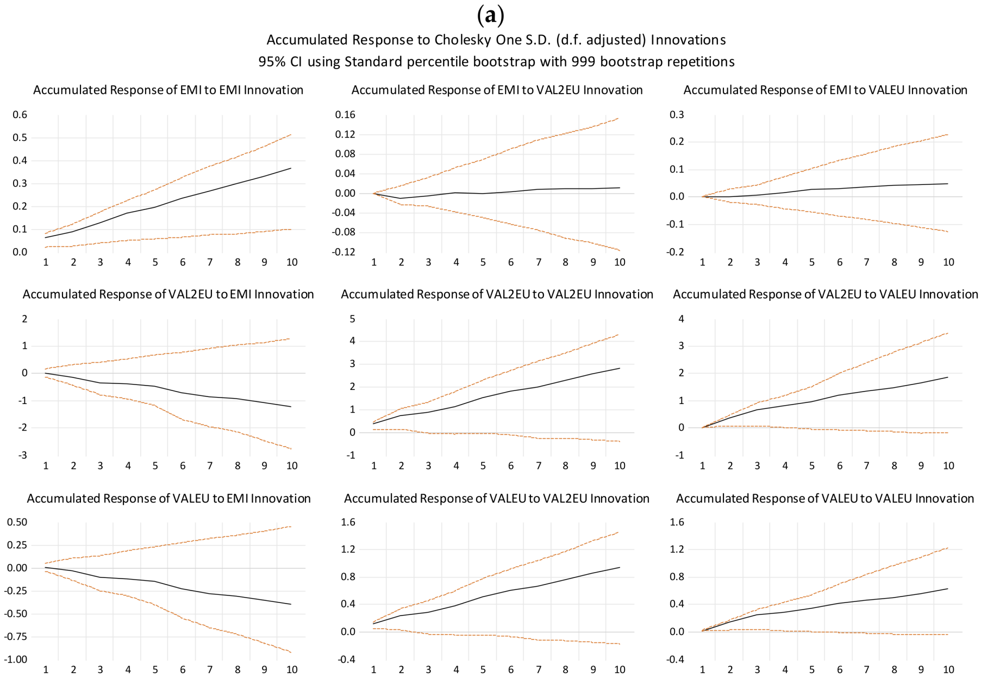
For the LDCs and carbon emissions, the equivalent variable is confirmed as I(1) and the year 1999 is the structural break identified. The same result is confirmed for the case of the agricultural income with a structural break traced in the year 2004. For the EU, all the respective variables are found to be I(1) with the years 2005 and 2007, respectively, to be identified as structural breaks. The food crisis (2007), the Kyoto Protocol (1996–1999 signing period), as well as the different financial crises may well interpret the breakpoints identified.

3.3. Impulse Response Analysis

The results of IRF analysis for the B-VAR models for both research areas, the LDCs and the EU, and for all the variables, are illustrated in Figure 2a and 2b, respectively. The regions surrounded by the red dotted lines indicate the posterior confidence intervals estimated for a 5% level of significance. The figures constructed were based on the Bayesian methodology using Gibbs sampling, while 1000 iterations were implemented to acquire the results [38–40].



(**a**)



(**b**)

Figure 2. (**a**) Impulse response analysis of the model variables for a ten-period time horizon or the LDCs. (**b**) Impulse response analysis of the model variables for a ten-period time horizon or the EU.

Based on the illustration of the previous figure, the responses of a variable to a shock (of a standard deviation) from other variables for the B-VAR model for a ten-period time horizon, within which this effect becomes less significant. This particular figure unveils the interlinkages among the model variables or the LDCs. The major findings provided by the aforementioned analysis are the following: An innovation in the emissions leads to a decrease in the agricultural income that is not fading within the ten periods, a result that confirms inefficiency in the efforts for climate change mitigation in terms of income effects. More specifically, based on our findings, a decrease in emissions generated by enteric fermentations is coupled by a decrease in agricultural income, a result that validates a failure in the objective of ecoefficiency. On the other hand, an innovation in value added is accompanied by a slight decrease in emissions generated by enteric fermentation. What is more the innovation in the square of value added leads to a slight increase in emissions generated by enteric fermentation, confirming the non-validity of the U-pattern of the environmental Kuznets curve. Conflicting results were derived for different developing countries, which may be attributed either to the methodology or the regional entity used as a research area [45,46].

The situation is significantly different for the case of the EU. The results are illustrated in the next Figure 2b.

An innovation in emissions generated by enteric fermentation entails a decrease in agricultural income for both the first and the square of the variable, while the emissions generated by enteric fermentation is decreasing in innovation occurrences of both variables employed, reflecting the variability in agricultural income. What is more the EKC hypothesis can be rejected, a result that is in line with some works and not with others, but certainly the climate change mitigation and adaptation strategy seem to be vital in the interlinkages developed [47–49].

3.4. Variance Decomposition Analysis

An alternative methodology to detect the interlinkages among the model variables to be estimated based on the BVAR methodology is the Forecast Error Variance Decomposition Analysis the results of which are illustrated in Tables 3 and 4 for LDCs and the EU, respectively [50–52].

Table 3. Forecast Variance Decomposition (FVED) analysis for a ten-time period horizon and the LDCs.

	Variance Decomposition of VADL		
	VADL	**EMI**	**VADL2**
1	100.0000	0.000000	0.000000
2	99.39371	0.392220	0.214074
3	97.70229	1.400428	0.897285
4	95.26713	2.751638	1.981234
5	92.39760	4.221321	3.381077
6	89.32276	5.653920	5.023317
7	86.19809	6.951129	6.850781
8	83.12297	8.055826	8.821199
9	80.15687	8.938899	10.90423
10	77.33205	9.589652	13.07830
	Variance Decomposition of EMI		
	VADL	**EMI**	**VADL2**
1	0.000000	100.0000	0.000000
2	0.053390	99.94364	0.002970
3	0.212939	99.78069	0.006376
4	0.474414	99.51838	0.007208
5	0.829778	99.16415	0.006068
6	1.270730	98.72226	0.007012
7	1.789329	98.19410	0.016575
8	2.377786	97.57928	0.042930
9	3.028251	96.87651	0.095241
10	3.732675	96.08412	0.183205

Table 3. *Cont.*

	Variance Decomposition of VADL2		
	VADL	**EMI**	**VADL2**
1	0.000000	0.000000	100.0000
2	0.163026	0.252150	99.58482
3	0.570995	1.042343	98.38666
4	1.218075	2.367871	96.41405
5	2.082154	4.191653	93.72619
6	3.128474	6.457918	90.41361
7	4.312343	9.097584	86.59007
8	5.582968	12.03307	82.38396
9	6.887412	15.18390	77.92869
10	8.174130	18.47231	73.35356

EMIL denotes CO_2e for LDCS, EMIEU denotes CO_2e for EU, VAL denotes value added by agriculture for LDCS, VAEU denotes value added by agriculture, ΔEMIL ΔVAL ΔEMIEU ΔVAEU denotes the first differences.

Based on our findings, the interlinkages among the model variables are validated also with the FEVD methodology. The agricultural income variability interpretation by emissions generated by enteric fermentation is increasing, while in the tenth period, it reaches 20%. On the other hand, the emissions generated by enteric fermentation are interpreted by agricultural income, with an increasing rate reaching 35% in the tenth period. As far as the square of agricultural income, it seems to interpret almost half of the emission variability (only 18%).

Table 4. Forecast Error Variance Decomposition (FEVD) for a ten-time period horizon for EU countries.

	Variance Decomposition of EMIEU		
	EMIEU	**VAL2EU**	**VALEU**
1	70.58440	16.83577	12.57983
2	56.20259	24.17349	19.62392
3	45.97577	28.76420	25.26003
4	44.10802	29.82690	26.06508
5	43.38882	30.48412	26.12706
6	43.71350	30.53114	25.75536
7	45.87152	29.62558	24.50290
8	47.58596	28.92753	23.48652
9	47.82270	28.90423	23.27307
10	48.02201	28.87470	23.10330
	Variance Decomposition of VAL2EU		
	EMIEU	**VAL2EU**	**VALEU**
1	10.75408	45.08675	44.15918
2	6.513600	44.90754	48.57886
3	9.204746	43.22259	47.57267
4	11.61745	42.36195	46.02061
5	8.438216	43.37513	48.18665
6	7.483579	43.48588	49.03054
7	7.900617	43.33397	48.76541
8	7.836282	43.40417	48.75955
9	7.497365	43.45368	49.04895
10	7.536840	43.40093	49.06223

Table 4. *Cont.*

	Variance Decomposition of VALEU		
	EMIEU	**VAL2EU**	**VALEU**
1	8.260094	45.39321	46.34670
2	4.768531	44.95771	50.27375
3	6.229328	43.77199	49.99868
4	7.660582	43.32319	49.01622
5	5.564302	43.91868	50.51702
6	4.861758	43.91307	51.22517
7	5.050269	43.83203	51.11771
8	4.949976	43.89664	51.15338
9	4.666852	43.91331	51.41984
10	4.630180	43.88072	51.48910

EMIL denotes CO_2e for LDCS, EMIEU denotes CO_2e for EU, VAL denotes value added by agriculture for LDCS, VAEU denotes value added by agriculture, ΔEMIL ΔVAL ΔEMIEU ΔVAEU denotes the first differences.

On the other hand, the FEVD estimation results for the EU countries are synopsized in Table 4.

The findings for the EU are significantly different since the variability of emissions generated by enteric fermentation, as well as the agricultural income association, is by far more significant compares to the LDCs. The specific results do not validate the efficiency of the agricultural policy in terms of ecoefficiency.

The last but certainly not least step in our analysis involves the model evaluation performance for the two group of countries with different philosophies and perceptions of climate change mitigation practices. The results are provided in Tables 5 and 6 for the LDCs and EU, respectively.

Table 5. B-VAR forecast statistics of the different prior distributions for the model variables for LDCs.

Variable	RMSE	MAE
VADL	0.007165	0.006070
EMI	0.060794	0.045630
VADL2	0.000318	0.000222

Notes: The table shows one-year ahead and two-year ahead forecasts. RMSE: root mean square error; MAE: Mean Average Error.

Table 6. B-VAR forecast statistics of the different prior distributions for the model variables for EU countries.

Variable	RMSE	MAE
VALEU	0.570113	0.489277
EMIEU	0.186186	0.154723
VALEU2	0.017916	0.013457

Notes: The table shows one-year ahead and two-year ahead forecasts. RMSE: root mean square error; MAE: Mean Average Error.

A good performance is validated for LDCs as well as or EU the results of which are provided in the previous tables.

4. Discussion

The present paper aims to identify and quantify the interlinkages of environmental degradation—economic performance in the agriculture of EU and LDCs.

Our findings in both cases validate the existence of an association, though the pattern of relationship differs given the different practices and strategies adopted by the two different groups of countries. The index used as a proxy for environmental degradation is emissions generated by enteric fermentation in carbon dioxide emissions equivalent per 1000 hectare of pasture. In addition, as a proxy for agricultural income, we selected the value added generated by agriculture, as well as the square of the same variable, in order to define the pattern of their relationship. Starting from the breakpoint ADF unit root test, all the variables employed in the model for both groups of countries are I(1), and thus non-stationary in levels and stationary in first differences.

The major findings involve the structural break detection for the variables, that is, 1999 and 2004 for the environmental degradation and agricultural income for the LDCs and 2008 and 2007 of the respective variables for EU. The global food crisis caused by fossil fuels and the use of fertilizers is reflected in the structural breaks identified for the EU countries, while, for the LDCs, the year 2004 reflects the efforts initiated to modernize agriculture due to low productivity, and 1999 is the preliminary period in which the LDCs initiated their entrance into the United Nations Framework Convention on Climate Change. In addition, in the year 2001, the LDCs Expert Group (LEG) was established in order to regulate the adoption of national plans for climate change mitigation.

The small number of data amplified the authors' decision to adopt the BVAR methodology that has validated the variables interlinkages, though the pattern of the relationship estimated is different. The interlinkages are identified by the impulse response analysis for the LDCs, which actually does confirm the non-validity of the environmental Kuznets curve pattern since it increases with the agricultural income and decreases with the square of agricultural income, a result that is not in line with previous studies [19,21,22]. A potential interpretation is the countries included in the sample as well as the methodology, that is, BVAR, which is more reliable, while, according to the authors' view, the fact that enteric fermentation is employed as a proxy for environmental degradation is another plausible explanation. The fact that the relationship initially decreases and then increases demonstrates the need for the adoption of practices that assist climate change mitigation, such as the type of feed, the change in the rumen environment, along with breed substitution and genetic manipulation. The emissions regulation is also related to cost and therefore is an impediment for the LDCs. More specifically, the improved feed and feed supplements are difficult to be used by low-income farmers in developing countries. What is more the production of less emitted feed for livestock may well be restrained due to land and water scarcity, coupled with inefficient irrigated systems [19,21,50–56].

On the other hand, for the EU-27 case, the previous literature is characterized by conflicting results. In the present manuscript, an innovation in the value added (as well as the square of the variable) leads to a decrease in carbon emissions generated by enteric fermentation, a result that contradicts previous studies [16,17]. There is currently a lack of focused studies on enteric fermentation specifically within EU countries, leaving limited evidence to facilitate a well-documented comparison with our findings. Our results, however, do not fully support the effectiveness of existing agro-environmental policies, as they fall short of achieving the intended eco-efficiency objectives.

The GHG reduction target for achieving zero-carbon agriculture by 2050 is indeed highly ambitious, with current reductions falling significantly short of what is necessary. This underscores the need for policymakers to identify the most polluting agricultural activities and establish targeted mitigation goals. Effective strategic planning will require not only the adoption of new initiatives, such as defining specific measures and updating legal frameworks, but also focused actions in high-emission areas to ensure substantial reductions.

The same results are confirmed by the Variance Decomposition Analysis, implying that in LDCs compared to the EU, the climate change mitigation measures taken cannot maintain the productivity in the case of livestock. This is an expected result given that the major objective of policymakers for those countries is poverty alleviation and food security, making it extremely difficult to tackle environmental problems effectively as well.

5. Conclusions

This study explores the environmental impact of enteric fermentation in livestock production, alongside the economic value it generates in both the EU and LDCs. The analysis utilizes a Bayesian Vector Autoregression (BVAR) methodology, which provides a more robust performance compared to traditional models like Vector Autoregression (VAR) and the Vector Error-correction Model (VECM). The research identifies significant relationships between the variables studied, with structural breaks quantified to reflect the impact of initiatives undertaken in both regions.

Interestingly, the results challenge the environmental Kuznets curve, which hypothesizes an inverted U-shaped relationship between economic growth and environmental degradation, as proposed by Stern. This suggests that stronger economic incentives may be necessary to enhance policy effectiveness and promote eco-efficiency. The distinctive characteristics of livestock production in the EU and LDCs should be carefully considered when shaping agricultural policies, with a strong emphasis on farmer education as a critical factor for success. Additionally, corporate management practices must be tailored to address the unique needs, strengths, and challenges of livestock businesses in these two diverse regions.

Above all, a significant issue that has to be highlighted here is that the EU's approach is more technology-driven, with policies promoting innovative feed additives, precision farming, and financial incentives to encourage methane reduction. In contrast, LDCs focus on capacity-building and low-cost practices due to resource constraints. The EU's policy measures are likely to yield faster reductions in methane emissions due to advanced technologies and substantial funding. In LDCs, the impact of policies is slower but crucial for addressing long-term food security and environmental resilience. Both approaches highlight the importance of tailoring climate policies to local economic and environmental contexts, underscoring the diverse pathways required to address global agricultural emissions effectively.

A key limitation of this study is the small sample size, which influenced the selection of the BVAR methodology. Future research could address this constraint by employing panel data analysis, allowing for a deeper exploration of the relationship between economic and environmental performance. Such an approach would yield a more robust understanding of the underlying dynamics and potentially offer more generalizable findings. Additionally, future studies could broaden the scope to include other agricultural emission sources, such as those from fertilizer use or land use changes, to provide a more comprehensive assessment of agriculture's environmental impact across different regions.

Author Contributions: Conceptualization, E.Z.; methodology, E.Z.; software, E.Z.; validation, E.Z., C.M., S.G. and G.A.; formal analysis, E.Z.; investigation, E.Z., C.M. and G.A.; resources, E.Z., C.M. and G.A.; data curation, E.Z., S.G. and S.S.; writing—original draft preparation, E.Z., C.M., S.G., S.S. and G.A.; writing—review and editing, E.Z., C.M. and G.A.; supervision, E.Z.; project administration, E.Z., C.M., S.G., S.S. and G.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Data Availability Statement: https://www.fao.org/faostat/en/#data (accessed on 22 September 2024).

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

The EU Countries Group

Austria, Belgium, Bulgaria, Croatia, the Republic of Cyprus, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, and Sweden.

The LDCs Group

Comoros, the Democratic Republic of the Congo, Djibouti, Eritrea, Ethiopia, Ethiopia PDR, Gambia, Guinea, Guinea-Bissau, Haiti, Kiribati, the Lao People's Democratic Republic, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mozambique, Myanmar, Nepal, Niger, Rwanda, Sao Tome and Principe, Senegal, Sierra Leone, Solomon Islands, Somalia, South Sudan, Sudan, Sudan (former), Timor-Leste, Togo, Tuvalu, Uganda, the United Republic of Tanzania, Vanuatu, Yemen, and Zambia.

References

1. IPCC. *Climate Change 2014: Mitigation of Climate Change*; Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Farahani, E., Kadner, S., Seyboth, K., Adler, A., Baum, I., Brunner, S., Eickemeier, P., et al., Eds.; Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change; Cambridge University Press: Cambridge, UK; New York, NY, USA, 2014.
2. FAO. *Agriculture, Forestry and Other Land Use Emissions by Sources and Removals by Sinks*; Climate, Energy and Tenure Division; FAO: Rome, Italy, 2014; 89p, 3.5 MB.
3. FAOSTAT. 2021. Available online: https://www.fao.org/3/cb3808en/cb3808en.pdf (accessed on 26 September 2022).
4. European Environment Agency (EEA). *Agriculture and Climate Change–Nitrous Oxide Emissions*; European Environment Agency (EEA): Copenhagen, Denmark, 2021.
5. Eurostat. Greenhouse Gas Emissions from Agriculture. 2020. Available online: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Archive:Agriculture_-_greenhouse_gas_emission_statistics (accessed on 24 June 2022).
6. IPCC. Refinements to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories. 2019. Available online: https://www.ipcc.ch/report/2019-refinement-to-the-2006-ipcc-guidelines-for-national-greenhouse-gas-inventories/ (accessed on 26 September 2022).
7. Murawska, A.; Prus, P. The Progress of Sustainable Management of Ammonia Emissions from Agriculture in European Union States Including Poland—Variation, Trends, and Economic Conditions. *Sustainability* **2021**, *13*, 1035. [CrossRef]
8. EEA, Air Quality in Europe—2019 Report. EEA Report No 10/2019, European Environment Agency. 2019. Available online: https://www.eea.europa.eu/publications/air-quality-in-europe-2019 (accessed on 22 July 2022).
9. EEA. EU Emissions of Ammonia. 2020. Available online: https://www.eea.europa.eu/en/analysis/indicators/greenhouse-gas-emissions-from-agriculture (accessed on 22 July 2022).
10. UNEP Annual Report 2022. 2022. Available online: https://wedocs.unep.org/bitstream/handle/20.500.11822/41679/Annual_Report_2022.pdf?sequence=3 (accessed on 29 October 2022).
11. European Environment Agency. Annual European Union Greenhouse Gas Inventory 1990–2017 and Inventory Report 2019: Submission under the United Nations Framework Convention on Climate Change and the Kyoto Protocol (EEA/PUBL/2019/051). European Environment Agency. 2019. Available online: https://www.eea.europa.eu/publications/european-union-greenhouse-gas-inventory-2019 (accessed on 16 June 2022).
12. Gerber, P.J.; Steinfeld, H.; Henderson, B.; Mottet, A.; Opio, C.; Dijkman, J.; Falcucci, A.; Tempio, G. *Tackling Climate Change Through livestock–A Global Assessment of Emissions and Mitigation Opportunities*; Food and Agriculture Organization of the United Nations (FAO): Rome, Italy, 2013.
13. Steinfeld, H.; Gerber, P.; Wassenaar, T.; Castel, V.; Rosales, M.; de Haan, C. *Livestock's Long Shadow*; FAO: Rome, Italy, 2006.
14. FAO. Available online: http://www.fao.org/gleam/ (accessed on 22 September 2024).
15. Leip, A.; Weiss, F.; Wassenaar, T.; Perez, I.; Fellmann, T.; Loudjani, P.; Tubiello, F.; Grandgirard, D.; Monni, S.; Biala, K. *Evaluation of the Livestock Sector's Contribution to the EU Greenhouse Gas Emissions (GGELS) Final Report*; European Commission, Joint Research Centre: Brussels, Belgium, 2010; 323p. Available online: http://ec.europa.eu/agriculture/analysis/external/livestock-gas/ (accessed on 27 October 2024).
16. Kleftodimos, G.; Kyrgiakos, L.S.; Kleisiari, C.; Tagarakis, A.C.; Bochtis, D. Examining farmers' adoption decisions towards precision-agricultural practices in Greek dairy cattle farms. *Sustainability* **2021**, *14*, 411. [CrossRef]
17. Tongwane, M.I.; Moeletsi, M.E. Emission factors and carbon emissions of CH4 from enteric fermentation of cattle produced under different management systems in South Africa. *J. Clean. Prod.* **2020**, *265*, 121931. [CrossRef]
18. IFAD. Rural Development Report 2021 | Transforming Food Systems for Rural Prosperity. 2021. Available online: https://www.ifad.org/documents/48415603/49775134/rdr2021.pdf/e6bad6ea-8dac-b478-a1c5-29522ba414cf?t=1726642391930 (accessed on 14 May 2022).
19. Food and Agriculture Organization of the United Nations. Methane Emissions in Livestock and Rice Systems. FAO. 2022. Available online: https://openknowledge.fao.org/server/api/core/bitstreams/805a3926-13e2-4d38-b926-315be0091b07/content (accessed on 22 September 2024).
20. Tongwane, M.I.; Moeletsi, M.E. Provincial cattle carbon emissions from enteric fermentation and manure management in South Africa. *Environ. Res.* **2021**, *195*, 110833. [CrossRef]

21. Orzuna-Orzuna, J.F.; Dorantes-Iturbide, G.; Lara-Bueno, A.; Mendoza-Martínez, G.D.; Miranda-Romero, L.A.; Hernández-García, P.A. Effects of dietary tannins' supplementation on growth performance, rumen fermentation, and enteric CH4 emissions in beef cattle: A meta-analysis. *Sustainability* **2021**, *13*, 7410. [CrossRef]
22. Ibidhi, R.; Kim, T.H.; Bharanidharan, R.; Lee, H.J.; Lee, Y.K.; Kim, N.Y.; Kim, K.H. Developing country-specific CH_4 emission factors and carbon fluxes from enteric fermentation in South Korean dairy cattle production. *Sustainability* **2021**, *13*, 9133. [CrossRef]
23. Food and Agriculture Organization of the United Nations. 2019. Available online: https://www.fao.org/family-farming/detail/en/c/1245425/ (accessed on 2 November 2022).
24. Mielcarek-Bocheńska, P.; Rzeźnik, W. Greenhouse gas emissions from agriculture in EU countries—State and perspectives. *Atmosphere* **2021**, *12*, 1396. [CrossRef]
25. Zafeiriou, E.; Azam, M. CO_2 emissions and economic performance in EU agriculture: Some evidence from Mediterranean countries. *Ecol. Indic.* **2017**, *81*, 104–114. [CrossRef]
26. Zafeiriou, E.; Sofios, S.; Partalidou, X. Environmental Kuznets curve for EU agriculture: Empirical evidence from new entrant EU countries. *Environ. Sci. Pollut. Res.* **2017**, *24*, 15510–15520. [CrossRef]
27. Aan den Toorn, S.I.; Worrell, E.; Van Den Broek, M.A. How much can combinations of measures reduce CH4 and nitrous oxide emissions from European livestock husbandry and feed cultivation? *J. Clean. Prod.* **2021**, *304*, 127138. [CrossRef]
28. Tagarakis, A.C.; Dordas, C.; Lampridi, M.; Kateris, D.; Bochtis, D. A Smart Farming System for Circular Agriculture. *Eng. Proc.* **2021**, *9*, 10. [CrossRef]
29. Fischer, A.; Edouard, N.; Faverdin, P. Precision feed restriction improves feed and milk efficiencies and reduces CH_4 emissions of less efficient lactating Holstein cows without impairing their performance. *J. Dairy Sci.* **2020**, *103*, 4408–4422. [CrossRef] [PubMed]
30. Ngwabie, N.M.; Jeppsson, K.H.; Gustafsson, G.; Nimmermark, S. Effects of animal activity and air temperature on CH_4 and ammonia emissions from a naturally ventilated building for dairy cows. *Atmos. Environ.* **2011**, *45*, 6760–6768. [CrossRef]
31. Mosnier, C.; Ridier, A.; Képhaliacos, C.; Carpy-Goulard, F. Economic and environmental impact of the CAP mid-term review on arable crop farming in South-western France. *Ecol. Econ.* **2009**, *68*, 1408–1416. [CrossRef]
32. Kleftodimos, G.; Gallai, N.; Rozakis, S.; Képhaliacos, C. A farm-level ecological-economic approach of the inclusion of pollination services in arable crop farms. *Land Use Policy* **2021**, *107*, 105462. [CrossRef]
33. Ocko, I.B.; Sun, T.; Shindell, D.; Oppenheimer, M.; Hristov, A.N.; Pacala, S.W.; Mauzerall, D.L.; Xu, Y.; Hamburg, S.P. Acting rapidly to deploy readily available CH4 mitigation measures by sector can immediately slow global warming. *Environ. Res. Lett.* **2021**, *16*, 054042. [CrossRef]
34. Goldstein, J.; Tyfield, D. Green Keynesianism: Bringing the entrepreneurial state back in (to question)? *Sci. Cult.* **2018**, *27*, 74–97. [CrossRef]
35. Tienhaara, K. Regulatory chill in a warming world: The threat to climate policy posed by investor-state dispute settlement. *Transnatl. Environ. Law* **2018**, *7*, 229–250. [CrossRef]
36. Gurbuz, I.B.; Nesirov, E.; Ozkan, G. Does agricultural value-added induce environmental degradation? Evidence from Azerbaijan. *Environ. Sci. Pollut. Res.* **2021**, *28*, 23099–23112. [CrossRef]
37. Prastiyo, S.E.; Irham; Hardyastuti, S.; Jamhari. How agriculture, manufacture, and urbanization induced carbon emission? The case of Indonesia. *Environ. Sci. Pollut. Res.* **2020**, *27*, 42092–42103. [CrossRef]
38. Dogan, E.; Inglesi-Lotz, R. The impact of economic structure to the environmental Kuznets curve (EKC) hypothesis: Evidence from European countries. *Environ. Sci. Pollut. Res.* **2020**, *27*, 12717–12724. [CrossRef] [PubMed]
39. Doğan, N. The impact of agriculture on CO_2 emissions in China. *Panoeconomicus* **2019**, *66*, 257–271. [CrossRef]
40. Liu, X.; Zhang, S.; Bae, J. The impact of renewable energy and agriculture on carbon dioxide emissions: Investigating the environmental Kuznets curve in four selected ASEAN countries. *J. Clean. Prod.* **2017**, *164*, 1239–1247. [CrossRef]
41. Sun, C.; Zhang, F.; Xu, M. Investigation of pollution haven hypothesis for China: An ARDL approach with breakpoint unit root tests. *J. Clean. Prod.* **2017**, *161*, 153–164. [CrossRef]
42. Lütkepohl, H. Vector autoregressive models. In *Handbook of Research Methods and Applications in Empirical Macroeconomics*; Edward Elgar Publishing: Cheltenham, UK, 2013.
43. Ivanov, V.; Kilian, L. A practitioner's guide to lag order selection for VAR impulse response analysis. *Stud. Nonlinear Dyn. Econom.* **2005**, *9*. [CrossRef]
44. Giannone, D.; Reichlin, L.; Sala, L. VARs, common factors, and the empirical validation of equilibrium business cycle models. *J. Econom.* **2006**, *132*, 257–279. [CrossRef]
45. Arellano, M.; Bond, S.R. Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Rev. Econ. Stud.* **1991**, *58*, 277–297. [CrossRef]
46. Kang, S.H.; Islam, F.; Tiwari, A.K. The dynamic relationships among CO_2 emissions, renewable and non-renewable energy sources, and economic growth in India: Evidence from time-varying Bayesian VAR model. *Struct. Change Econ. Dyn.* **2019**, *50*, 90–101. [CrossRef]
47. Pearan, H.H.; Shin, Y. Generalized impulse response analysis in linear multivariate models. *Econ. Lett.* **1998**, *58*, 17–29. [CrossRef]
48. Brahmasrene, T.; Huang, J.C.; Sissoko, Y. Crude oil prices and exchange rates: Causality, variance decomposition and impulse response. *Energy Econ.* **2014**, *44*, 407–412. [CrossRef]

49. Selcuk, M.; Gormus, S.; Guven, M. Do agriculture activities matter for environmental Kuznets curve in the Next Eleven countries? *Environ. Sci. Pollut. Res.* **2021**, *28*, 55623–55633. [CrossRef] [PubMed]
50. Lütkepohl, H. Variance Decomposition. In *Macroeconometrics and Time Series Analysis. The New Palgrave Economics Collection*; Durlauf, S.N., Blume, L.E., Eds.; Palgrave Macmillan: London, UK, 2010. [CrossRef]
51. Ali, G.; Ashraf, A.; Bashir, M.K.; Cui, S. Exploring environmental Kuznets curve (EKC) in relation to green revolution: A case study of Pakistan. *Environ. Sci. Policy* **2017**, *77*, 166–171. [CrossRef]
52. Jakada, A.H.; Mahmood, S.; Ahmad, A.U.; Garba Muhammad, I.; Aliyu Danmaraya, I.; Sani Yahaya, N. Driving Forces of CO_2 Emissions Based on Impulse Response Function and Variance Decomposition: A Case of the Main African Countries. *Environ. Health Eng. Manag. J.* **2022**, *9*, 223–232. [CrossRef]
53. Sarkodie, S.A.; Ozturk, I. Investigating the environmental Kuznets curve hypothesis in Kenya: A multivariate analysis. *Renew. Sustain. Energy Rev.* **2020**, *117*, 109481. [CrossRef]
54. Sarkodie, S.A.; Strezov, V. A review on environmental Kuznets curve hypothesis using bibliometric and meta-analysis. *Sci. Total Environ.* **2019**, *649*, 128–145. [CrossRef]
55. Harsányi, E.; Bashir, B.; Almhamad, G.; Hijazi, O.; Maze, M.; Elbeltagi, A.; Alsalman, A.; Enaruvbe, G.O.; Mohammed, S.; Szabó, S. GHGs Emission from the Agricultural Sector within EU-28: A Multivariate Analysis Approach. *Energies* **2021**, *14*, 6495. [CrossRef]
56. Gorodnichenko, Y.; Lee, B. Forecast error variance decompositions with local projections. *J. Bus. Econ. Stat.* **2020**, *38*, 921–933. [CrossRef]