Assessing environmental and economic dynamics in the EU agri-food sector: The impact of imports through a BVAR analysis

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Abstract

The study investigates the environmental impact of the EU agri-food sector, focusing on emissions per capita and their relationship with economic growth through a Bayesian Vector Autoregression (BVAR) framework. It reveals that greening efforts in the sector have not been matched by sufficient economic growth, challenging the Environmental Kuznets Curve (EKC) hypothesis. Despite progress in sustainable practices, economic expansion has fallen short of offsetting environmental costs, with imports playing a critical role. The Carbon Border Adjustment Mechanism (CBAM) under the EU Green Deal highlights the need to address trade-related emissions. The study calls for future research to develop a comprehensive index incorporating diverse variables to better assess sustainability efforts in the agri-food sector.

Keywords: *Agricultural income, Digitalization, Farmers' education, Green deal, Climate change action.*

1. Introduction

The modern way of life worldwide exerts increasing pressure on natural resources, heightening concerns about their depletion. Rapid population growth and the intensification of industrial and agricultural production amplify these concerns, particularly in light of projections that global food production must double by 2050 to meet the needs of a population expected to reach approximately 9.8 billion by 2050 and 11.2 billion by 2100. These pressures are exacerbated by inefficiencies and losses in the agri-food supply chain, contributing to food

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waste and environmental degradation. According to FAO, one-third of the world's food is lost, impacting 800 million people suffering from hunger, with Europe alone generating 88 million tons of food waste annually. Despite these challenges, the existing literature addressing the intersection of green practices, technological advancements, and economic growth in the agri-food sector remains limited. Current studies largely focus on consumer behavior and demand for environmentally conscious products. Limited work examines the broader systemic changes required to balance economic growth with environmental sustainability, particularly through innovative methodologies or the integration of technology with green practices. Furthermore, the interdependencies between green supply chains, economic efficiency, and sustainability goals are underexplored, especially concerning how policy frameworks like the EU's Common Agricultural Policy (CAP) and global initiatives like the Green Deal address these challenges.

This work aims to bridge this gap by analyzing how green practices, coupled with modern technology, can transform the agri-food sector to achieve eco-efficiency. Eco-efficiency, a term popularized by Schaltegger and Sturm in 1992, links economic and environmental performance by emphasizing sustainable value creation while reducing environmental harm. The study further examines how technological paradigms, such as precision agriculture, can enhance productivity and profitability without exacerbating environmental degradation. Additionally, it evaluates policy impacts, particularly those stemming from the CAP (2023-2027) and Green Deal, on agri-food sector sustainability. The novelty of this study lies in its methodological and analytical approach. Employing advanced techniques such as Bayesian Vector AutoRegression (BVAR), it investigates the economic and environmental interlinkages within the agri-food sector. The study uniquely considers the role of import indices in the context of the Green Deal's Carbon Border Adjustment Mechanism, a measure yet to be widely implemented in the sector. Unlike prior studies focusing narrowly on producer behavior or consumer demand, this research adopts a systemic view, encompassing supply chain coordination, trade liberalization impacts, and policy frameworks to propose actionable pathways for sustainable development in the agri-food sector.

2. Existing Literature

Current agri-food systems face multifaceted challenges that necessitate urgent reform to achieve global food security and sustainability. Food insecurity and malnutrition persist, particularly in low- and middle-income countries (LMICs), where limited resources and inefficient agricultural practices exacerbate systemic vulnerabilities. Compounding these issues are entrenched profit-driven models that resist the adoption of sustainable practices, prioritizing short-term economic gains over long-term ecological stability. Climate change, coupled with economic crises and unpredictable environmental conditions, underscores the critical need for systemic transformation in the agri-food sector (FAO, 2022; IPCC, 2023).

The inefficiencies of current agri-food systems contribute significantly to food waste and environmental degradation. Globally, one-third of food production is lost or wasted, affecting approximately 800 million people who experience hunger. In Europe alone, food waste through the supply system amounts to 88 million tons annually, highlighting the scale of inefficiency (European Commission, 2022). LMICs face additional challenges, including inadequate infrastructure, limited technological access, and economic constraints that hinder their capacity to implement sustainable agricultural practices (Godfray *et al.*, 2021).

Climate change presents a profound threat to global agriculture, with rising temperatures, shifting growing seasons, and extreme weather events disrupting food production patterns. The adverse effects of climate change are particularly pronounced in LMICs, where adaptive capacity is limited (IPCC, 2023). Economic crises and public health emergencies, such as the COVID-19 pandemic, further exacerbate these vulnerabilities, revealing the fragility of global food systems (Benton & Bailey, 2022). Collectively, these challenges necessitate a transformative approach that integrates sustainability into every aspect of the agri-food sector.

International initiatives, such as the Sustainable Development Goals (SDGs), and regional policies, including the European Union's Common Agricultural Policy (CAP) and the Green Deal, provide critical frameworks for addressing these issues. The SDGs, particularly Goals 2 ("Zero Hunger") and 12 ("Responsible Consumption and Production"), advocate for systemic reform to enhance sustainability, equity, and resilience in food systems (UN, 2023). The CAP (2023-2027) allocates significant resources—approximately 23 billion euros—to promote environmentally friendly practices, focusing on climate change mitigation and biodiversity conservation. The Green Deal aims to transition Europe into a sustainable, resilient, and digital economy, with measures such as the Carbon Border Adjustment Mechanism designed to reduce carbon leakage and promote global adoption of sustainable practices (European Commission, 2023).

Technological innovation plays a pivotal role in transforming agri-food systems. Precision agriculture, leveraging data analytics, sensors, and automation, has demonstrated substantial potential to enhance productivity while minimizing environmental impacts (Gebbers & Adamchuk, 2023). Renewable energy integration, intelligent agricultural equipment, and the adoption of bio-pesticides and organic fertilizers represent essential advancements for achieving sustainability (Pretty *et al*., 2023). Digital technologies, including blockchain, artificial intelligence, and machine learning, further optimize supply chain efficiency, enhance transparency, and reduce waste (Tian, 2023). These technologies collectively facilitate the transition to eco-efficient systems that balance economic growth with environmental preservation.

Abbate *et al*. (2023) emphasize the dual transition towards digitalization and sustainability within the agri-food sector, identifying the critical role of technological advancements in addressing systemic inefficiencies and reducing environmental footprints. Similarly, Belaud *et al*. (2019) highlight the potential of Big Data applications in promoting sustainability through better by-product management in supply chains.

Industry 4.0 technologies, such as automation and IoT, are pivotal in enabling these transformations. Ojo *et al*. (2018) discuss the implications of Industry 4.0 for sustainable food supply chains, stressing its role in improving traceability and reducing food loss. Qian *et al*. (2020) further elaborate on food traceability systems from diverse stakeholder perspectives in the European Union and China, underscoring its global relevance.

Despite the transformative potential of these technologies, their adoption remains uneven across regions, presenting significant challenges. Low-income countries face infrastructural deficits, such as inadequate internet connectivity, lack of electrification, and high costs associated with digital tools, which hinder the deployment of advanced technologies and exacerbate global inequities in agricultural productivity (Lipper *et al*., 2017). Smallholder farmers, who constitute a significant portion of global agricultural producers, often lack access to financial resources, technical expertise, and training required to adopt digital solutions (Ferroni & Zhou, 2017). Without targeted interventions, these disparities are likely to persist. Additionally, some innovations remain in developmental stages or require customization to address diverse agroecological contexts, which limits their scalability and relevance to different farming systems.

The socio-economic implications of digital transformation in agriculture are profound, offering both opportunities and risks. AI-based demand forecasting optimizes supply chains by aligning production with consumption patterns, thereby reducing food waste and leading to cost savings and environmental benefits (Chen *et al*., 2020). Digital platforms provide access to new markets, financial services, and supply chain information, empowering farmers and agribusinesses. However, the shift toward technology-intensive farming risks marginalizing smaller farmers who lack the means to compete with larger agribusinesses. This underscores the need for inclusive policies to ensure equitable benefits from these advancements (Pingali *et al*., 2019).

Sustainability remains a cornerstone of digital transformation in agri-food systems. Innovations offer promising avenues to minimize the environmental footprint of agriculture. Precision irrigation and AI-driven crop monitoring contribute to lower emissions by optimizing resource use. Research indicates potential reductions of up to 20% in greenhouse gas emissions (Rose *et al.*, 2021). Blockchain technology supports compliance with environmental standards through transparent monitoring and smart contracts, incentivizing sustainable practices across supply chains (Feng *et al.*, 2020).

The convergence of digital transformation and sustainability represents a dynamic and evolving frontier. Realizing the full potential of these innovations will require concerted efforts. Governments and international organizations must develop frameworks that encourage technology adoption while protecting the interests of smallholder farmers. Subsidies, tax incentives, and funding for infrastructure development can address existing gaps. Collaborative efforts among technologists, agronomists, environmental scientists, and policymakers are essential to create integrated solutions. Investments in education and training programs will enable farmers to leverage digital tools effectively, fostering widespread adoption and equitable benefits. By aligning technological advancements with sustainability objectives, the digital transformation of agri-food systems has the potential to revolutionize global agriculture, ensuring food security, economic development, and environmental stewardship.

The concept of eco-efficiency, which emphasizes the integration of economic value creation with environmental preservation, offers a guiding framework for addressing these challenges. Empirical studies demonstrate that eco-efficient practices can significantly reduce greenhouse gas emissions, enhance resource efficiency, and improve economic resilience (Stern, 2023). However, achieving eco-efficiency requires a paradigm shift among industry stakeholders, prioritizing long-term value creation and sustainability over immediate profitability (Schaltegger & Sturm, 2023).

Empirical studies underscore the transformative potential of eco-efficient practices in addressing the interconnected challenges of environmental sustainability and economic viability. Such practices have been shown to significantly reduce greenhouse gas emissions, enhance resource efficiency, and strengthen economic resilience (Stern, 2023). For instance, innovations in waste-to-energy systems, precision manufacturing, and circular economy models contribute to reduced resource depletion and lower environmental footprints. Research highlights that industries adopting these strategies report not only a decrease in operational costs but also an improvement in market competitiveness, as consumers increasingly demand sustainable products and services (Porter & Kramer, 2023).

Achieving eco-efficiency, however, requires more than incremental adjustments; it necessitates a profound paradigm shift among industry stakeholders. Organizations must prioritize long-term value creation, which balances profitability with environmental stewardship and social responsibility. This shift often involves rethinking traditional business models to incorporate principles of sustainability at every stage, from product design to end-of-life management (Schaltegger & Sturm, 2023). Effective adoption of eco-efficiency also depends on fostering a culture of innovation, where sustainability-driven solutions are incentivized and supported.

The role of policy frameworks and regulatory mechanisms is critical in driving this transformation. Governments and international bodies must establish supportive policies, such as tax incentives for green technologies, subsidies for renewable energy adoption, and stringent emissions regulations. These measures create an enabling environment for industries to align their objectives with broader sustainability goals. Public-private partnerships can further amplify these efforts by mobilizing resources and facilitating knowledge sharing, accelerating the transition to eco-efficient practices (Bocken *et al.*, 2023; Rochas-Serano *et al.*, 2024).

Education and stakeholder engagement are also pivotal. Building awareness among consumers, suppliers, and employees about the benefits of eco-efficiency fosters collective action. Transparent communication and reporting on sustainability performance, guided by frameworks such as the Global Reporting Initiative (GRI) and the Task Force on Climate-related Financial Disclosures (TCFD), ensure accountability and reinforce trust among stakeholders (Elkington, 2023).

For EU recently, the adoption of precision agriculture within the EU has grown significantly, as a means of ecoefficiency aligning closely with the EU's sustainability goals while it was spurred by supportive policies like the Common Agricultural Policy (CAP) and the European Green Deal. CAP has encouraged farmers to implement sustainable and resource-efficient practices, including variable-rate application systems and remote sensing tools. This shift is further supported by the Horizon Europe program, which funds innovative projects such as SmartAgriHubs to develop scalable and adaptive solutions for the region's diverse agricultural needs. As a result, precision agriculture adoption across the EU is projected to reach over 25% of farms by 2025, with a compound annual growth rate exceeding 12% (European Commission, 2023).

The precise application of water, fertilizers, and pesticides minimizes waste and runoff, preserving soil health and promoting biodiversity. A recent study by the Joint Research Centre (JRC) found that precision irrigation reduced water use by 20% without compromising crop yields. Furthermore, practices such as controlled traffic farming and optimized nutrient management contribute to a reduction in greenhouse gas emissions, supporting the European Green Deal's objective of achieving climate neutrality by 2050.

In addition, the EU's dependency on agricultural imports by improving domestic production efficiency and supply chain resilience. Enhanced yield predictability and optimized resource management make the EU more self-sufficient in critical commodities, such as grains, oilseeds, and proteins. In a global context characterized by geopolitical uncertainties and trade disruptions, these advancements bolster the EU's food security. Additionally, blockchain technology integrated into precision farming enhances supply chain transparency, enabling traceability and reinforcing consumer trust in sustainably produced EU goods. This combination of innovation and sustainability has strengthened the EU's position as a global leader in exporting high-quality agricultural products.

While existing literature has explored various aspects of sustainability in the agri-food sector, significant gaps remain. Research on the interdependencies between green practices, technological innovation, and economic growth is limited, particularly regarding their combined impact on global trade and supply chain dynamics. Additionally, the role of policy frameworks, such as the Green Deal and CAP, in shaping international trade and sustainability outcomes requires further exploration (Vermeir & Verbeke, 2023).

This study addresses these gaps by employing advanced quantitative methodologies to analyze the economic and environmental interlinkages within the agri-food sector. By examining the role of policy measures, such as the Carbon Border Adjustment Mechanism and import indices, this research provides a comprehensive understanding of how international trade and sustainability goals intersect. The findings aim to inform policymakers and industry stakeholders on actionable pathways to achieve a resilient, sustainable agri-food sector capable of meeting future demands while safeguarding environmental integrity.

The paper is organized as follows: section 2 describes the data and the methodology employed, section 3 highlights the results of the methodology, section 4 discusses the results and the lastly section 5 presents the conclusions and policy implications, specifying the scientific value, practicality, as well as the limitations of the study.

3. Data - Methodology

3.1. *Data*

The objective of this manuscript is to achieve its aim by developing a model that integrates key factors, including carbon emissions generated by the agri-food sector, value added per capita, and imports within the EU or the specific sector under review. In alignment with the greening objectives mandated by the Common Agricultural Policy (CAP), this study aims to model and estimate the relationship between the sector's greening initiatives and its economic growth. The research builds a theoretical foundation by exploring eco-efficiency, which focuses on aligning economic output with reduced environmental impact, and the Environmental Kuznets Curve (EKC), which suggests that environmental degradation initially rises with economic growth but eventually declines at higher income levels (Panayotou, 1993; Schaltegger & Sturm, 1990).

While eco-efficiency emphasizes optimizing the ratio of economic output to environmental impact through deliberate actions and technological innovation, the EKC examines the trajectory of environmental degradation across stages of economic development. Together, these frameworks offer complementary perspectives on the dynamics of environmental and economic sustainability. Eco-efficiency underscores the necessity of proactive measures to reduce environmental impact, challenging the optimistic assumption inherent in the EKC that economic growth alone will eventually lead to reduced environmental degradation. By prioritizing intentional strategies and innovations, eco-efficiency addresses the urgent need for sustainable practices in ways that the EKC framework, reliant on natural economic trajectories, does not fully encompass.

To comprehensively capture the interlinkages among these variables, the study formulates the following empirical function:

$$f(EMIti, VAAi, Impp) \qquad (1)$$

where EMIti, denotes the emissions per capita
GDP generated by agriculture per capita
Imp denotes import index

The dataset employed in this study encompasses annual data spanning the period 1990-2020, with a specific focus on the European Union (EU) treated as a single entity. The data were obtained from FAOSTAT and include three key variables: emissions per capita in the agri-food sector (utilized as a proxy to evaluate the greening of the agri-food sector), the GDP per capita share attributed to agriculture (indicative of economic growth within the EU), and an index reflecting changes in the cost, insurance, and freight (c.i.f.) values of imports, all denominated in US dollars. These variables were chosen to provide a comprehensive understanding of the interplay between sustainability, economic performance, and trade in the EU's agri-food systems.

The selection of emissions per capita as a proxy for the greening of agri-food systems is grounded in the pivotal role of reducing greenhouse gas (GHG) emissions in achieving sustainability. The transition to more sustainable practices within agri-food systems is intrinsically linked to mitigating climate change and environmental degradation. Despite policy efforts and technological advancements, the pace of this transition has lagged behind expectations, particularly in comparison to the broader decline in total EU GHG emissions. This discrepancy underscores the persistent challenges in decarbonizing the agri-food sector.

FAOSTAT data reveal the substantial environmental footprint of agri-food systems, extending beyond agricultural production to include processing, transportation, and consumption stages. These downstream activities significantly contribute to the sector's overall emissions, highlighting the need for a systems-wide approach to sustainability. Globally, agri-food systems account for approximately 30% of total GHG emissions, illustrating their critical role in addressing climate goals. Within the EU, this sector remains a focal point for achieving targets under the European Green Deal, which aims for climate neutrality by 2050.

The inclusion of GDP per capita share generated by agriculture provides insight into the economic contributions of the sector, reflecting its role in supporting livelihoods and driving regional development. Simultaneously, the index tracking changes in c.i.f. values of imports captures the trade dimension of the EU's agri-food systems, offering a perspective on how external dependencies and global market dynamics intersect with sustainability objectives.

By integrating these variables, the dataset serves as a robust foundation for analyzing the complex interactions among environmental performance, economic resilience, and trade patterns in the EU's agri-food systems over three decades. This longitudinal perspective enables the identification of trends, challenges, and opportunities critical for steering the sector toward a more sustainable and equitable future.

Analyzing the emissions trajectory and the proportional contribution of agri-food systems reveals a consistent downward trend since 2000, though progress has been constrained by continued fossil fuel combustion for energy. Simultaneously, non-food-related emissions within the sector have surged, increasing by 50% since 2000. In absolute terms, per capita emissions attributed to agri-food systems decreased from 2.4 t CO_2eq/cap in 2000 to 2.0 t CO_2eq/cap by 2020, reflecting a modest but meaningful reduction over two decades.

In the European Union (EU), agri-food systems remain a significant contributor to the region's carbon footprint, accounting for approximately 33% of total EU emissions in 2020. These emissions encompass a wide range of activities that extend beyond agricultural production. Specifically, they include emissions generated within the farm gate, those arising from land-use changes such as deforestation and soil degradation, and emissions linked to pre- and post-production processes, including food processing, transportation, packaging, and waste management.

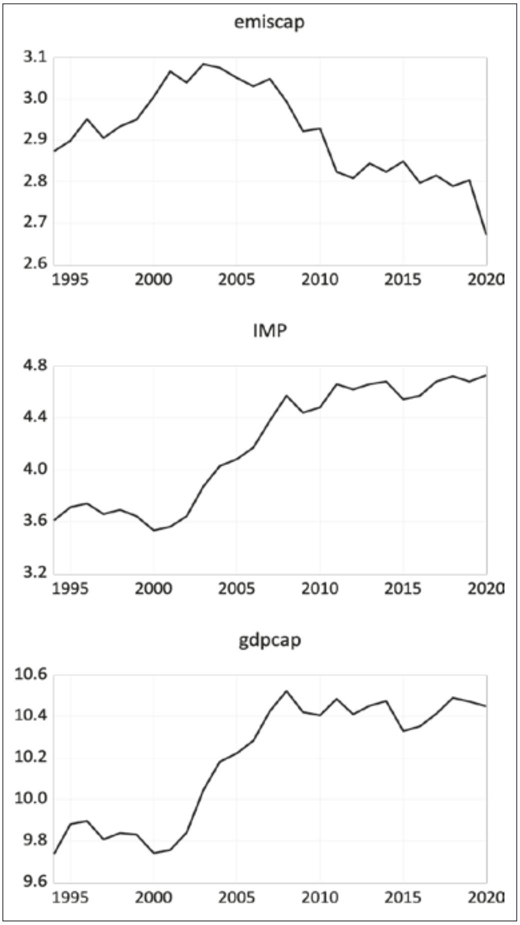
The comprehensive calculations that inform these figures integrate data from multiple reputable sources. Key datasets include the United Nations Statistical Division (UNSD), the International Energy Agency (IEA), and third-party analytical tools. Additionally, the PRIMAP-hist dataset v2.4 has been instrumental in synthesizing historical emissions data and providing a consistent basis for comparison across time and regions (UNSD, 2022; IEA, 2021; Gütschow *et al.*, 2021). These datasets collectively enable a granular examination of emissions drivers and trends, helping policymakers and stakeholders identify critical intervention points.

Despite the observed reductions in per capita emissions, the agri-food sector's emissions trajectory highlights ongoing challenges. The increasing prevalence of energy-intensive agricultural practices and the expansion of non-food agricultural activities—such as biofuel production—have offset some of the gains achieved through efficiency improvements and sustainable practices. Furthermore, emissions from land-use change remain a persistent issue, particularly in regions where agricultural expansion continues to drive deforestation and habitat loss.

The evolution of the data employed and for the reference period 1990-2020 are illustrated in the next Figure 1.

As illustrated in the figure the GDP share generated by agriculture is stationary and slightly increasing for a time period of five years a sharp increase in 2000 and after that an unstable movement implicitly oscillations are evident without a concise growth.

Figure 1 - Evolution of the model variables employed (1990-2020).



On the other the emissions are increasing with a declining trend in the first two decades though then the slope of the curve is changing and has become sharply decreasing within the last decade.

Regarding the role of imports, the evolution pattern is similar to that of the gdp share though the import index is increasing even in the year 2018 though this is not the case for the GDP per capita that is decreasing.

Evidently and based on the above figure the emissions intensity is slowing down without a clear positive income effect to be validated and also with a significant value of the import index rejecting the hypothesis of ecoefficiency. The graphical illustration shows that exploring the interlinkages of the particular variables could highlight the path for ecoefficiency in EU agri-food sector.

3.2. *Methodology*

The BVAR methodology is the framework employed for the above-mentioned variables (Sarantis & Stewart, 1995; Yan et al., 2022; Tsioptsia *et al*., 2022; Narayan & Popp, 2013). The Bayesian Vector Autoregression (BVAR) model builds upon the standard Vector Autoregression (VAR) framework by incorporating Bayesian statistical principles, offering several advantages and operating under key assumptions. BVAR assumes that the variables in the system are interdependent, meaning they influence each other dynamically over time. For example, in this study, emissions, economic growth, and trade are presumed to have mutual, time-dependent relationships. Additionally, the model typically assumes stationarity, which means that the time-series data have statistical properties, such as mean and variance, that do not change over time. If the data are not stationary, transformations like differencing are applied to stabilize these properties. Another foundational assumption of BVAR is the incorporation of prior information, which is drawn from theoretical knowledge, past studies, or expert opinion. This prior knowledge guides the estimation process and is particularly valuable when the available data is limited or noisy. Furthermore, BVAR operates within a probabilistic framework, explicitly accounting for uncertainty in its predictions and parameter estimates. Instead of providing single-point forecasts, it offers probabilistic intervals, such as confidence or credible intervals, to represent the range of likely outcomes (Koop, 2003).

BVAR holds several advantages over traditional VAR models. First, it addresses the issue of overfitting, a common problem in VAR models that arises due to the need to estimate a large number of parameters, especially when the dataset is small. By incorporating Bayesian priors, BVAR constrains parameter estimates and reduces the risk of overfitting, resulting in more robust model performance. Second, BVAR often yields improved forecasting accuracy because it integrates prior knowledge with observed data, making it particularly effective when dealing with short or noisy datasets. Third, the Bayesian approach adeptly handles multicollinearity, a situation where predictor variables are highly correlated, which can destabilize traditional VAR models. Finally, BVAR offers greater interpretability and flexibility, allowing researchers to transparently quantify uncertainty in predictions and adjust the model to incorporate different prior beliefs or assumptions (Karlsson, 2013).

To make this more accessible to non-specialists, BVAR can be thought of as combining the strengths of observed data and expert knowledge. If traditional VAR is like navigating without a map and relying solely on what you observe, BVAR is akin to navigating with both a map and the terrain in view. The “map” (prior knowledge) complements the “terrain” (data), particularly when the data is sparse or noisy, resulting in a more informed and reliable decision-making process.

Prior to the analysis implementation, we conducted a Break Unit root test in order to test the rank of variables’ integration (Bloor & Matheson, 2011). The next step in our analysis involved the implementation of the BVAR methodology in order to detect the interlinkages among green practices implementation and economic growth in the agri-food sector as well as to unveil the role of imports (Nyangchak, 2022). The Bayesian VAR is employed as it is considered a more efficient methodology compared to the classical VAR model. The mathematical form of a BVAR model does not differ though the parameters’ estimation and interpretation is different. More specifically, the BVAR models incorporate prior information about model parameters allowing the authors to get more reliable results given that this process provides stability in the parameter estimation. The prior specification employed in our BVAR model is Minnesota while the posteriors’ estimation is based on Maximum likelihood function (Sarantis & Stewart, 1995; Yan *et al*., 2022; Tsioptsia *et al*., 2022; Narayan & Popp, 2013; Nyangchak, 2022).

A tractable posterior density function is generated being similar to the one of the prior with

Minnesota algorithm for the parameter under review (Yan *et al*., 2022). The Bayesian Vector Autoregression (BVAR) model with the Minnesota prior addresses the overfitting and instability challenges of traditional VAR models, especially when data is limited. Introduced by Litterman (1986), the Minnesota prior shrinks coefficients toward a random walk baseline, where a variable's own lags are assumed to have more influence than lags of other variables. This shrinkage reduces overparameterization and improves forecast accuracy.

The Minnesota prior's key feature is its hyperparameter, controlling the degree of shrinkage. Tighter priors pull coefficients closer to zero, favoring simplicity unless the data strongly supports otherwise. Its computational efficiency stems from assuming a diagonal prior covariance matrix, avoiding complex methods like MCMC.

Studies, including Litterman (1986) and Banbura *et al*. (2010), highlight its effectiveness in forecasting macroeconomic variables and handling high-dimensional VARs. This makes the Minnesota prior a powerful tool for balancing flexibility and parsimony in systems like environmental and economic modeling.

Thus, the hyperparameter value is equal to the value of the prior μ while the covariance prior is non zero. Furthermore, the matrix of error terms is Null, under the condition that the variance-covariance matrix is diagonal. The next step in our BVAR analysis involves the specification of the target parameter, having incorporated a set of hyperparameters variables (Yan *et al*., 2022; Tsioptsia *et al*., 2022; Narayan & Popp, 2013). The small value of $\lambda 1$, is attributed to the fact that the prior information is more efficient than the sample information. The parameter, $\lambda 2$ is the regulator of the lag significance of the other variables and the parameter $\lambda 3$ reflects the impact of the exogenous variable on the endogenous variable. Finally, $\lambda 4$ unveils the data scale and variability differences, with the lag loss to be either linear when $\lambda 4=1$, harmonic or geometric in case $\lambda 4>0$ (Yan *et al*., 2022; Tsioptsia *et al*., 2022; Narayan & Popp, 2013).

The last step in our analysis involves the impulse response function estimation (IRF) for each variable as well as the Forecast Variance Decomposition Analysis (FEVD). Impulse Response Analysis is a fundamental tool in econometrics and time series analysis for examining the dynamic interactions among variables in multivariate models. It evaluates how a shock to one variable propagates through the system over time, affecting other variables. The methodology has evolved significantly, with notable contributions by Koop *et al*. (1996) and Pesaran and Shin (1998), who expanded its applicability to nonlinear and linear multivariate frameworks, respectively.

Koop *et al*. (1996) introduced Impulse Response Analysis for nonlinear multivariate models, addressing limitations of traditional linear approaches. Their work provided a robust framework for analyzing systems where relationships between variables may vary depending on the state of the system. For instance, in macroeconomic models, the effects of policy changes might differ during periods of economic expansion versus recession. Their methodology captures these complexities, making it particularly useful for analyzing real-world economic dynamics where nonlinearity is prevalent.

Pesaran and Shin (1998) advanced the field by developing Generalized Impulse Response Analysis (GIRA) within linear multivariate models. Unlike traditional approaches that rely on orthogonalization via Cholesky decomposition—which imposes a specific ordering of variables—GIRA provides a flexible and ordering-invariant methodology. This innovation is particularly valuable in settings where the causal ordering of variables is ambiguous or controversial, such as in macroeconomic studies examining interactions between monetary policy, inflation, and output. By allowing shocks to be modeled in a less restrictive manner, GIRA facilitates more realistic and interpretable analyses. The practical implications of these developments are extensive. In policy analysis, IRF enables researchers and policymakers to simulate the effects of interventions, such as fiscal stimulus or monetary tightening, on key economic indicators over time. In financial markets, it aids in understanding how shocks to interest rates or stock prices influence interconnected markets. Moreover, the adaptability of these methodologies to both linear and nonlinear systems has broadened their applicability across diverse fields, including environmental modeling, health economics, and industrial organization (Koop *et al*., 1996; Pesaran *et al*., 1998).

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 further quantify the contribution rates of all variables to the impact on the dependent variable (Ivanov & Kilian, 2005; Brahmasrene *et al*., 2014; Jakada *et al*., 2022; Lanne & Nyberg, 2016; Pesaran & Shin, 1998).

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 (Pesaran & Shin, 1998):

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(y_i-\bar{y})^2}{n}} \quad (17)$$

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n}|y_i-\bar{y}|}{n} \quad (18)$$

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

4. Results

The first step in our analysis, namely the break unit root test employed has provided the following results as synopsized in Table 1.

Based on the aforementioned findings for the EU all the respective variables are found to be I(1) with the years 1999 and 2002 respectively to be identified as structural breaks. The Kyoto protocol (1996-1999 signing period) as well as the different financial crises may well interpret the breakpoints identified.

The Impulse Response analysis was also employed in order to detect and quantify the interlinkages among the variables employed. Based on our findings the response of agricultural income due to an innovation to the emissions is decreasing with a steady declining rate the slope becomes steeper after the five years while a balance and a constant route is evident within the last few years. In addition, the response of emissions to an innovation in agricultural income is initially increasing at an increasing rate while this change in the mid-term since the curvature of the response changes and from curved becomes cave. The results are provided in Figure 2.

The figures constructed were based on the Bayesian methodology Gibbs sampling while 1000 iterations were implemented to acquire the results (Solazzo & Pierangeli, 2016; Kasztelan *et al*., 2019; Kovalenko *et al*., 2021).

Based on the Impulse Response Analysis (as illustrated in Figure 3), an innovation in emissions seem to steadily decrease the emissions rate for a 20-period studied. On the other hand, an innovation in imports and GDP share seems to in total decrease the emission for the time period studied though in a limited way with imports to be more effective than GDP share. Regarding the response of imports on the innovation of the emissions is initially increasing with a decreasing rate and then decreasing after a 1-period time.

The GDP increases with a declining trend for a period of twenty years while the emissions increase with a declining trend in the first decade though then the slope of the curve is changing and becomes increasing.

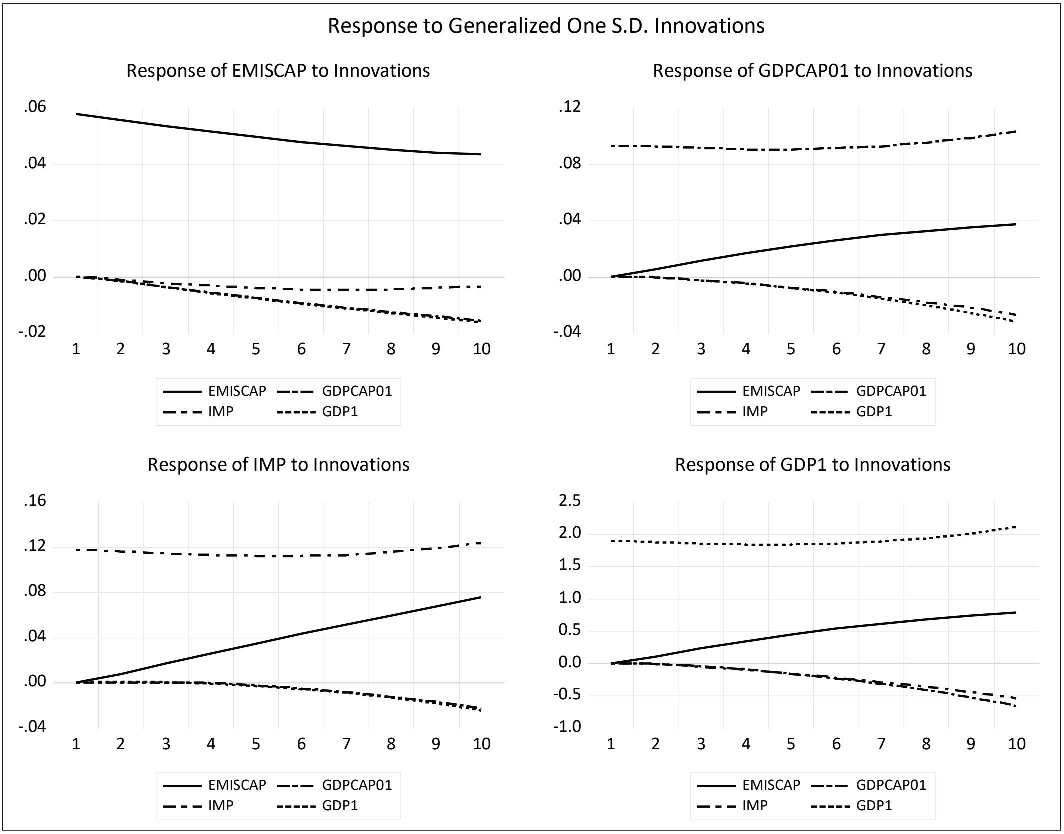
Based on the above results it becomes evident that natural processes, such as livestock manure, enteric fermentation, and land use, contribute

Table 1 - ADF break unit root results.

Variables	*ADF Break Unit Root*	*Break date*
CEM	-3.33 (0.778)	1999
ΔCEM	-5.50*** (0.000)	2001
GDP	-3.81 (0.48)	2002
ΔGDP	-4.82*** (0.0)	2003
IMP	-4.35* (0.06)	2002
Δ IMP	-5.03*** (000)	2000

**** reject of unit root test for 1% level of significance with critical values -4.94, -4.44, -4.19 for 1,5 and 1% level of significance CEM denotes carbon emission per capita for agrifood system for EU, GDP denoted GDP per capita, IMP denotes the import index for EU and ΔCEM ΔGDP, ΔIMP denotes the first differences of the variables respectively*

Figure 2 - Impulse – response analysis of the model variables (10-period).

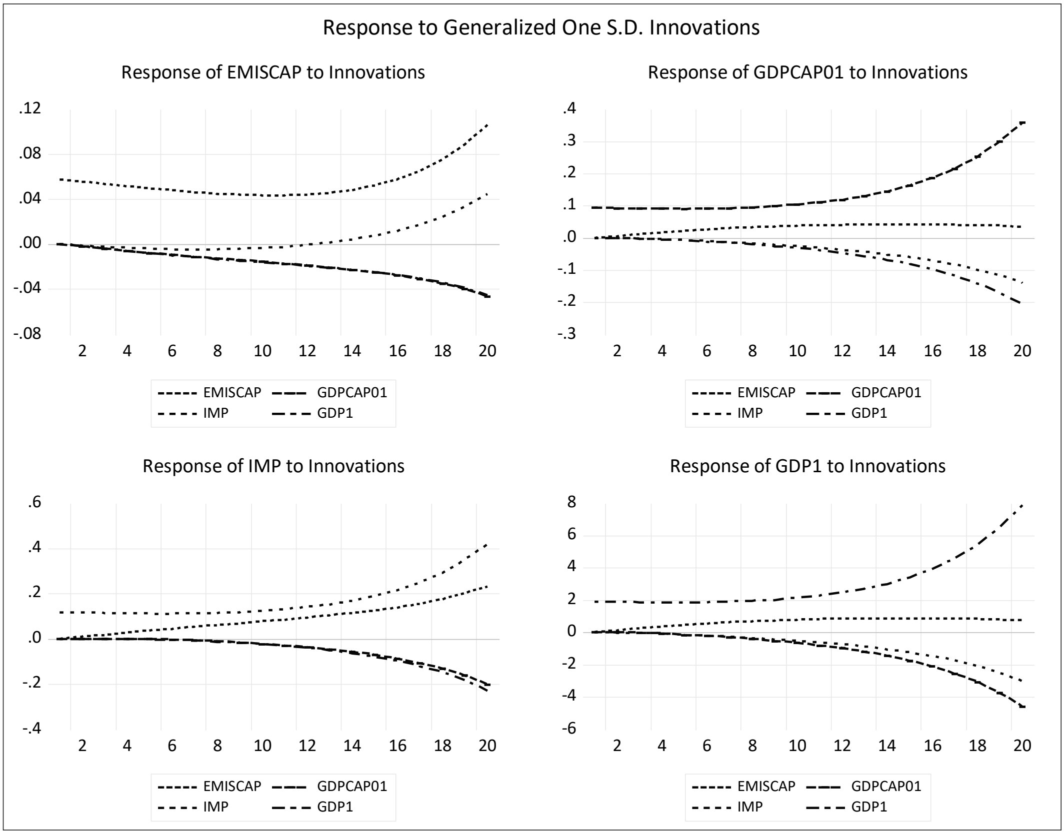


greatly to methane emissions, making agriculture a major part of the agri-food sector hard to abate. What is more, fertilizers hurt the climate through the release of nitrous oxide. There are however solutions to reduce emissions from agrifood systems, such as the introduction of environmentally friendly and efficiency improvement through automation. The particular solutions could enable a reduction in the emission intensity (that is the level of GHGs released per kg of product) of specific food commodities. EU production of livestock products, have decreased in emission intensity in recent decades. According to calculations by the European Topic Centre on Climate Change Mitigation, policies and measures currently in place are expected to cause only a 1.5 % reduction in the agricultural sector's emissions between now and 2040. This result implies that more steps should be taken to enhance the efficient limitation of environmental degradation. On the other hand, the response of imports on innovation of emissions tends to increase linearly the index related to the imports while innovations on GDP decrease the imports throughout the period studied. Last but not least the response of GDP share per capita generated by agriculture in case of innovations in emissions leads to an increase in GDP with a declining rate while stability becomes evident within ten years.

This means that the greening of the agrifood sector cannot provide a steadily increasing growth and therefore more steps need to be taken in order ecoefficiency to become an achievable objective in the EU.

When the impulse response analysis involves twenty periods an innovation in imports causes an increase in emissions while an innovation in GDP share generated by agriculture causes a decrease in emissions. The significant change becomes more evident after the 12th period. What

Figure 3 - Impulse – response analysis of the model variables (20-period).



is more the innovation in emissions has a slight impact on GDP and the same variable is slightly decreasing for innovation in imports.

The forecast error variance decomposition analysis reveals more insightful results after 20 periods compared to 10. Specifically, for emissions volatility, only 10% is attributable to GDP volatility, while 4.2% can be explained by volatility in imports. These findings highlight the limited interconnectivity between the variables analyzed, suggesting that the relationships among emissions, GDP, and imports are not strongly interdependent within the framework employed. For a 10-period reference, the explanatory power of the variables is even more constrained, providing less meaningful insights into their dynamics. Importantly, these patterns remain consistent across other variables in the study, indicating that the observed trends are robust but that further investigation is needed to identify additional factors influencing emissions and their interrelationship with economic growth and trade. This underscores the need to explore alternative causal pathways to effectively prioritize environmental sustainability in the agri-food sector while mitigating potential adverse income effects. Another notable observation concerns the limited impact of imports on both income and environmental outcomes. This suggests that while trade policies and imports play a role, their influence is not as pronounced as other factors. These findings highlight the need for a multifaceted approach to address environmental issues in the agri-food sector, emphasizing strategies that integrate sustainability goals without compromising economic resilience. Further research should aim to uncover additional drivers and refine the policy framework to enhance the sector's capacity for sustainable growth.

Another step involves Sims-ZHA analysis

Table 2 - Generalized FEVD Analysis (Lanne and Nyberg, 2016).

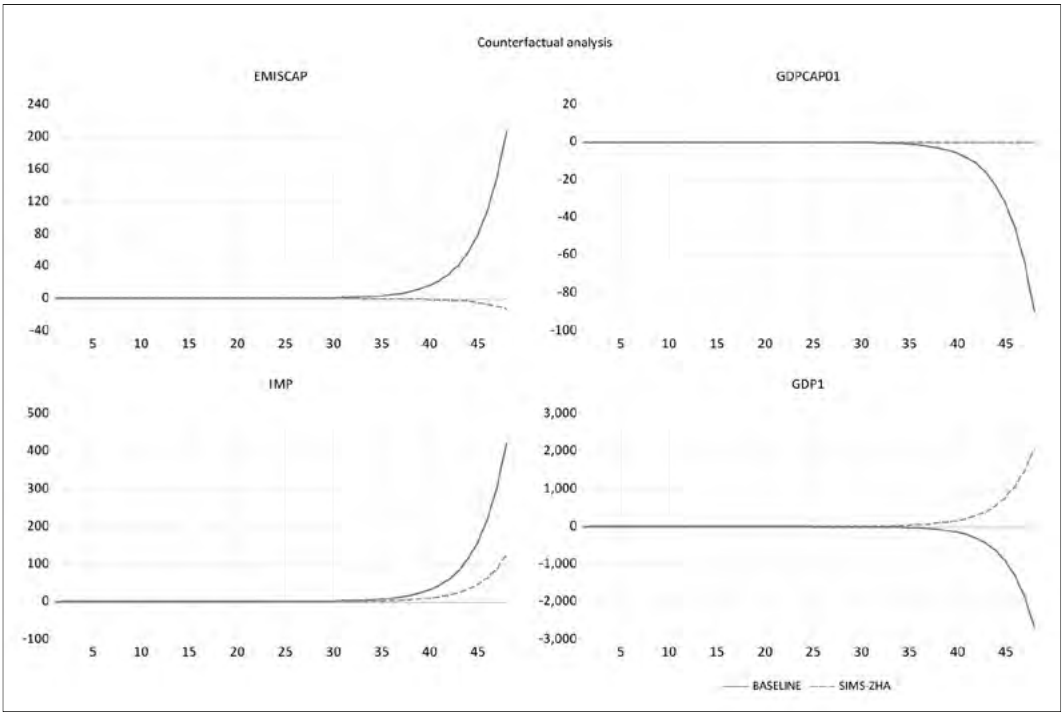
Variance decomposition of EMISCAP				
	EMISCAP	GDPcap^2	GDPCAP	IMP
1	100.0000	0.000000	0.000000	0.000000
2	99.89138	0.044249	0.039874	0.024496
3	99.54465	0.190690	0.176762	0.087895
4	98.97621	0.435923	0.410263	0.177600
5	98.21348	0.772122	0.734676	0.279725
6	97.28471	1.190762	1.142862	0.381661
7	96.21727	1.683418	1.627002	0.472306
8	95.03644	2.242190	2.178953	0.542421
9	93.76440	2.859942	2.790446	0.585209
10	92.41928	3.530395	3.453117	0.597210
11	91.01400	4.248007	4.158355	0.579633
12	89.55533	5.007555	4.896887	0.540223
13	88.04295	5.803291	5.657999	0.495764
14	86.46903	6.627492	6.428330	0.475143
15	84.81894	7.468288	7.190241	0.522534
16	83.07365	8.306819	7.920033	0.699503
17	81.21525	9.114289	8.586779	1.083678
18	79.23585	9.850376	9.153248	1.760528
19	77.14858	10.46541	9.580789	2.805225
20	74.99640	10.90863	9.839142	4.255823

Variance decomposition of GDPCAP01				
	EMISCAP	GDP1	GDPCAP01	IMP
1	0.000000	0.000000	100.0000	0.000000
2	0.154966	0.004576	99.83738	0.003075
3	0.595799	0.038281	99.33147	0.034455
4	1.265362	0.121255	98.50143	0.111957
5	2.091764	0.274871	97.38292	0.250447
6	3.001357	0.520989	96.01495	0.462707
7	3.923122	0.881538	94.43593	0.759410
8	4.791541	1.377864	92.68173	1.148867
9	5.548732	2.029866	90.78475	1.636656
10	6.146201	2.854688	88.77408	2.225034
11	6.546498	3.864792	86.67666	2.912050
12	6.724978	5.065280	84.51935	3.690395
13	6.671703	6.450544	82.33160	4.546150
14	6.393230	8.000724	80.14825	5.457796
15	5.913635	9.678952	78.01132	6.396094
16	5.273828	11.43080	75.96988	7.325488
17	4.528206	13.18741	74.07690	8.207485
18	3.738328	14.87284	72.38304	9.005789
19	2.964463	16.41468	70.92878	9.692072
20	2.257090	17.75502	69.73728	10.25061

Variance decomposition of GDP1				
	EMISCAP	GDP1	GDPCAP01	IMP
1	0.000000	100.0000	0.000000	0.000000
2	0.153244	99.84115	0.002055	0.003556
3	0.590360	99.35067	0.023941	0.035028
4	1.257957	98.54816	0.082998	0.110881
5	2.088408	97.46837	0.198456	0.244765
6	3.012193	96.14865	0.391098	0.448059
7	3.961928	94.62539	0.682906	0.729778
8	4.874824	92.93233	1.096516	1.096329
9	5.694467	91.09992	1.654450	1.551167
10	6.372263	89.15551	2.377947	2.094284
11	6.868835	87.12451	3.285175	2.721483
12	7.155578	85.03225	4.388698	3.423478
13	7.216458	82.90641	5.692171	4.184963
14	7.049918	80.77950	7.186608	4.983977
15	6.670398	78.69060	8.846973	5.792024
16	6.108683	76.68547	10.63035	6.575495
17	5.410130	74.81400	12.47718	7.298694
18	4.630177	73.12509	14.31644	7.928298
19	3.827417	71.65961	16.07464	8.438342
20	3.055633	70.44365	17.68643	8.814286

Variance decomposition of IMP				
	EMISCAP	GDP1	GDPCAP01	IMP
1	0.000000	0.000000	0.000000	100.0000
2	0.205939	0.000505	0.001105	99.79245
3	0.836548	0.000367	0.001147	99.16194
4	1.874776	0.003656	0.001256	98.12031
5	3.277107	0.019844	0.007223	96.69583
6	4.983297	0.063195	0.028978	94.92453
7	6.921659	0.151912	0.079737	92.84669
8	9.013041	0.307231	0.175216	90.50451
9	11.17411	0.552406	0.332871	87.94061
10	13.32003	0.911452	0.571057	85.19746
11	15.36674	1.407475	0.908003	82.31779
12	17.23319	2.060448	1.360452	79.34591
13	18.84414	2.884310	1.941873	76.32968
14	20.13379	3.883472	2.660217	73.32252
15	21.05074	5.049137	3.515411	70.38471
16	21.56393	6.356276	4.497078	67.58271
17	21.66845	7.762474	5.583229	64.98584
18	21.38949	9.209932	6.740825	62.65976
19	20.78219	10.63122	7.928754	60.65784
20	19.92612	11.95813	9.103022	59.01272

Figure 4 - Sims-Zhu policy analysis results of the model variables.



through which we try to conclude how policy measures adoption on climate change would affect the behavior of the other variables. Based on policy measures taken for climate change mitigation we may conclude that the emissions become limited, the GDP share generated by agriculture is stabilized while the imports are increasing with a less steep upward trend. This result is significant since the proper climate change mitigation measures may lead to ecoefficiency. All the results are illustrated in next Figure 4.

The last but not least step in our analysis involves a forecast analysis (Figure 5). More specifically, the averages, and the actual values over the periods, provides a quick visual comparison of the model variables but in the present work we illustrate the result for the emissions generated by the agri-food sector in EU.

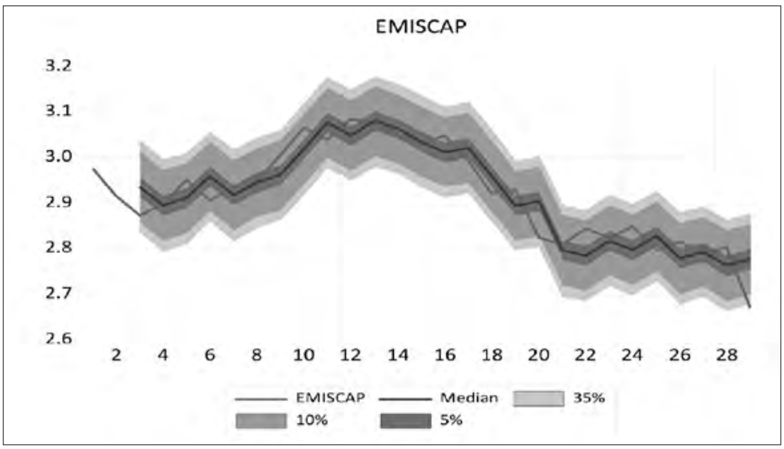


Figure 5 - Real and average values of the emissions generated by the estimated model.

Table 3 - Forecast Model's evaluation statistic results for all the variables.

Variable	*RMSE*	*MAE*	*MAPE*	*Theil*
EMISCAP	0.042251	0.034328	1.190075	0.007236
GDP1	1.530497	1.228946	1.187841	0.007351
GDPCAP01	0.075314	0.060488	0.594720	0.003694
IMP	0.093340	0.072838	1.766562	0.011057

The emission estimated based on the model lies within a band of 5% oscillation indicating that the model employed is accurate. The above findings are further validated with the indices provided in the table below including RMSE, MAE, MAPE and Theil validate model accuracy indices.

The following section provides a detailed interpretation of the derived results and outlines their policy implications. This analysis aims to translate the findings into actionable insights, offering a foundation for informed decision-making to address key challenges and opportunities identified in the study.

5. Discussion - Conclusions

Green and sustainable practices in the agri-food sector have become increasingly prevalent in modern societies, particularly within the European Union (EU). This trend is strongly supported by policies such as the Farm-to-Fork Strategy, which aligns with the Sustainable Development Goals (SDGs) to provide nutritious and affordable food for a growing global population. The EU's strategy specifically aims to create fair, healthy, and environmentally-friendly food systems. The EU's strategy aims to establish fair, healthy, and environmentally sustainable food systems. A cornerstone of this approach is the European Green Deal, which sets an ambitious goal of making Europe carbon neutral. This wide-ranging policy framework encompasses all sectors of the economy, with agriculture playing a pivotal role. Within the Green Deal, the Farm-to-Fork Strategy focuses on building sustainable food systems that protect human health, support society, and safeguard the environment. One of the Green Deal's key targets is to reduce greenhouse gas (GHG) emissions by 50–55% compared to 1990 levels, underscoring the EU's strong commitment to combating climate change and advancing sustainability throughout the agri-food sector (Belaud *et al*., 2019; Annosi *et al*., 2021; Notenbaert *et al*., 2020; Fanzo *et al*., 2020; FAOSTAT, 2018; Andrieu & Kebede, 2020). To achieve the ambitious targets set by the European Green Deal and the Farm-to-Fork Strategy, several key actions are essential within the agri-food sector. To minimize environmental and health impacts, a 50% reduction in the use and risk of chemical pesticides is essential. This requires promoting alternative pest management strategies and encouraging the adoption of safer, more sustainable solutions.

Simultaneously, nutrient losses—especially nitrogen and phosphorus—must be reduced by at least 50% to prevent water pollution and eutrophication, without compromising soil fertility. Achieving this will depend on improved nutrient management and the implementation of precision agriculture techniques.

Fertilizer use should also be decreased by at least 20% to curb environmental damage, particularly greenhouse gas emissions and soil degradation. This calls for optimized fertilization practices, including the use of organic and enhanced-efficiency fertilizers.

Furthermore, the sale of antimicrobials for farm animals and aquaculture must be halved to combat the escalating threat of antimicrobial resistance. This underscores the need for better animal husbandry, stronger biosecurity measures, and the development of effective alternative treatments. Expanding the area of farmland under organic farming to 25% by 2030 is crucial for promoting biodiversity, improving soil health, and reducing chemical inputs, thereby contributing to more sustainable food systems. These measures are vital for meeting the EU's sustainability goals, ensuring that the agri-food sector contributes to a healthier environment, more resilient food systems, and a reduced overall carbon footprint for agriculture (van Bers *et al*., 2019; Boix-Fayos & de Vente, 2023).

This study employs the Bayesian Vector Autoregression (BVAR) methodology to investigate the interlinkages between emissions per capita from the agri-food sector, used as a proxy for greening, and GDP per capita. The findings reveal that current efforts to achieve greening in the agri-food sector remain largely ineffective. While carbon emissions have decreased, these reductions are not accompanied by proportional improvements in economic efficiency. The EU's "Farm-to-Fork" strategy, a pivotal component of the Sustainable Development Goals (SDGs), seeks to deliver nutritious and affordable food while fostering sustainability. However, the progress achieved thus far is insufficient to meet these ambitious objectives.

The limitations of current greening efforts highlight the urgent need for policies that leverage the potential of digitalization and innovation. Precision mechanization, automation, and advanced data-driven decision-making systems present promising solutions to the sector's environmental and operational challenges. Real-time data acquisition and instantaneous information sharing can significantly enhance traceability, promoting greater sustainability and transparency across the agri-food supply chain. This is particularly important as consumers are increasingly concerned about the structure and integrity of these supply chains, especially in response to recurring food safety scandals and emerging risks over recent decades.

Advancing sustainable food systems requires a multifaceted approach that integrates technological innovation, consumer education, and coordinated efforts across stakeholders. Policymakers must create enabling environments for the adoption of digital tools, such as precision agriculture and blockchain, to improve resource efficiency and supply chain transparency. Education and training initiatives organized by cooperatives, research institutions, policymakers, and academics are critical for equipping farmers and other decision-makers with the knowledge needed to implement sustainable agricultural practices. Regulatory frameworks should also be strengthened to ensure that greening efforts align with broader economic and environmental goals.

The analysis of the impact of imports on carbon emissions reveals only a limited effect. Using Impulse Response Function (IRF) and Forecast Error Variance Decomposition (FEVD) methods, the study finds that although an increase in imports slightly elevates carbon emissions and reduces the agri-food sector's contribution to GDP, these effects are relatively minor. The FEVD analysis indicates that only 8.8% of emissions volatility can be attributed to changes in imports. This limited influence can be attributed, in part, to initiatives like the Carbon Border Adjustment Mechanism (CBAM), introduced under the EU Green Deal. CBAM imposes a carbon price on imports from countries with less stringent environmental standards, thereby reducing carbon leakage. However, additional trade restrictions within the agri-food sector could reduce imports further, potentially leading to significant economic repercussions. These include decreased production, reduced exports, higher food prices, increased food insecurity, lower farmer incomes, and potential GDP declines.

The results of this study align with and expand upon findings from prior research. Abbate *et al*. (2023) emphasize the importance of digital and sustainable transitions in the agri-food sector [Technological Forecasting and Social Change]. Similarly, Dora *et al*. (2021) propose a system-wide interdisciplinary framework for mitigating food loss and waste in supply chains [Industrial Marketing Management]. Belaud *et al*. (2019) explore the role of big data in sustainability management for agri-food supply chains [Computers in Industry]. Furthermore, Annosi *et al*. (2021) discuss the integration of digitalization to prevent food waste [Industrial Marketing Management].

In alignment with Ojo *et al*. (2018), this study underscores the transformative potential of Industry 4.0 technologies in achieving sustainable food supply chains. Additionally, Fanzo *et al*. (2020) highlight the role of decision-support tools, such as the Food Systems Dashboard, in informing better policy decisions.

The limited impact of imports on emissions is consistent with the findings of FAOSTAT (2018) regarding trade and sustainable agri-food systems. Furthermore, the challenges posed by policy lock-ins, as noted by Kuokkanen *et al*. (2017), and the need for innovative pathways, as discussed by Boix-Fayos and de Vente (2023), underscore the urgency of adopting transformative measures within the EU's Green Deal framework.

Based on the above, this study highlights the urgent need for transformative policies and innovative solutions to align the greening of the agri-food sector with economic growth. Policymakers must balance trade policies with sustainability goals, ensuring that mechanisms such as CBAM are complemented by investments in technology, education, and infrastructure. Only through coordinated actions and robust policy frameworks can the EU achieve the dual objectives of environmental sustainability and economic resilience within the agri-food sector.

The Farm-to-Fork strategy, a cornerstone of the Sustainable Development Goals (SDGs), aims to provide nutritious and affordable food on a global scale while promoting sustainability. Implemented across various stages of the EU agri-food industry, the strategy has made some progress, but achieving eco-efficiency in this sector demands additional efforts. This study's examination of the long-term interlinkages within the sector highlights the evolving nature of these relationships as the Green Deal advances and new data becomes available.

A key limitation of this study is its reliance on time series analysis that treats the EU as a single entity. While this approach provides valuable insights, effective policy solutions may require a more granular analysis at the member state level. Future research could address this by employing panel data analysis techniques, such as Dynamic Ordinary Least Squares (DOLS) or Fully Modified OLS, to gain a deeper understanding of the economic and environmental efficiency of policy measures. These methods could help identify the specific steps necessary to improve outcomes and ensure alignment with the targets set by the SDGs and the Green Deal.

Additionally, the role of imports in shaping the agri-food sector warrants further investigation. As the Green Deal progresses and import restrictions evolve, it will be crucial to understand their broader implications. In particular, future research should focus on the origins of imports from countries that do not adhere to emerging environmental standards. Expanding the dataset to include more detailed observations would allow researchers to capture the dynamics of the global agri-food market as it adapts to these changes.

This ongoing analysis will be instrumental in refining policies and practices to address the dual challenges of climate change and the transition to sustainable food systems. A more nuanced understanding of these interdependencies is critical for the formulation of integrated strategies that align environmental sustainability with economic resilience. Such an approach is instrumental in advancing the aims of the Farm-to-Fork Strategy, the Sustainable Development Goals (SDGs), and the European Green Deal.

References

Abbate S., Centobelli P., Cerchione R., 2023. The digital and sustainable transition of the agri-food sector. *Technological Forecasting and Social Change*, 187: 122222.

Akyazi T., Goti A., Oyarbide A., Alberdi E., Bayon F., 2020. A guide for the food industry to meet the future skills requirements emerging with industry 4.0. *Foods*, 9(4): 492.

Andrieu N., Kebede Y., 2020. *Agroecology and Climate Change: A case study of the CCAFS Research Program*. CCAFS Working paper.

Annosi M.C., Brunetta F., Bimbo F., Kostoula M., 2021. Digitalization within food supply chains to prevent food waste. Drivers, barriers and collaboration practices. *Industrial Marketing Management*, 93: 208-220.

Balwinder-Singh, Shirsath P.B., Jat M.L., McDonald A.J., Srivastava A.K., Craufurd P., Rana D.S., Singh A.K., Chaudhari, S.K., Sharma, P.C., Singh R., Jat H.S., Sidhu H.S., Gerard B., Braun H., 2020. Agricultural labor, COVID-19, and potential implications for food security and air quality in the breadbasket of India. *Agricultural Systems*, 185: 102954.

Bańbura M., Giannone D., Reichlin L., 2010. Large Bayesian vector auto regressions. *Journal of Applied Econometrics*, 25(1): 71-92.

Belaud J.P., Prioux N., Vialle C., Sablayrolles C.,

2019. Big data for agri-food 4.0: Application to sustainability management for by-products supply chain. *Computers in Industry*, 111: 41-50.

Bhatia M.S., Gangwani K.K., 2021. Green supply chain management: Scientometric review and analysis of empirical research. *Journal of cleaner production*, 284: 124722.

Bloor C., Matheson T., 2011. Real-time conditional forecasts with Bayesian VARs: An application to New Zealand. *The North American Journal of Economics and Finance*, 22(1): 26-42.

Boix-Fayos C., de Vente J., 2023. Challenges and potential pathways towards sustainable agriculture within the European Green Deal. *Agricultural Systems*, 207: 103634.

Brahmasrene T., Huang J.C., Sissoko Y., 2014. Crude oil prices and exchange rates: Causality, variance decomposition and impulse response. *Energy economics*, 44: 407-412.

Brown M., Jones J., 2013. *The predicted impacts of the proposed greening measures of the 2014 CAP reform on farming businesses in North Cornwall*, n. 355-2016-18198.

Cao Y., Mezzenga R., 2020. Design principles of food gels. *Nature Food*, 1(2): 106-118.

Czekaj S., Majewski E., Was A., 2013. The impact of the "greening" of the Common Agricultural Policy on the financial situation of Polish farms. *Applied Studies in Agribusiness and Commerce*, 7(2-3): 49-55.

Depetris-Chauvin N., Fernandez Olmos M., Hu W., Malorgio G., 2023. Costs and benefits of sustainability-oriented innovation in the agri-food industry: A review. *New Medit*, 22(3): 23-45.

De Schutter O., 2017. The political economy of food systems reform. *European Review of Agricultural Economics*, 44(4): 705-731.

Dora M., Biswas S., Choudhary S., Nayak R., Irani Z., 2021. A system-wide interdisciplinary conceptual framework for food loss and waste mitigation strategies in the supply chain. *Industrial Marketing Management*, 93: 492-508.

Dorninger C., Abson D.J., Apetrei C.I., Derwort P., Ives C.D., Klaniecki K., Lam D.P.M., Langsenlehner M., Riechers M., Spittler N., von Wehrden, H., 2020. Leverage points for sustainability transformation: a review on interventions in food and energy systems. *Ecological Economics*, 171: 106570.

EC-JRC/PBL, 2019. *Emission Database for Global Atmospheric Research (EDGAR)*, release version 4.2. http://Edgar.Jrc.Ec.Europa.Eu/Index.Php.

Ejsmont K., Gladysz B., Kluczek A., 2020. Impact of industry 4.0 on sustainability—bibliometric literature review. *Sustainability*, 12(14): 5650.

Fanzo J., Haddad L., McLaren R., Marshall Q., Davis C., Herforth A., Jones A., Beal T., Tschirley D., Bellows A., Miachon L., Gu Y., Bloem M., Kapuria A., 2020. The Food Systems Dashboard is a new tool to inform better food policy. *Nature Food*, 1(5): 243-246.

Fanzo J., McLaren R., Davis C., Choufani J., 2017. *Climate change and variability. What Are the Risks for Nutrition, Diets, and Food Systems.*

FAOSTAT, 2018. *Trade and sustainable agrifood systems: pathways of interaction*, https://www.fao.org/3/cb7270en/cb7270en.pdf accessed on October 1th, 2023.

FAOSTAT, 2022. Greenhouse gas emissions from agrifood systems Global, regional and country trends, 2000-2020, https://www.fao.org/3/cc2672en/cc2672en.pdf accessed at 2/28/2024.

Fielke S., Taylor B., Jakku E., 2020. Digitalisation of agricultural knowledge and advice networks: A state-of-the-art review. *Agricultural Systems*, 180: 102763.

Frías-Paredes L., Mallor F., Gastón-Romeo M., León T., 2018. Dynamic mean absolute error as new measure for assessing forecasting errors. *Energy conversion and management*, 162: 176-188.

Fuchs R., Brown C., Rounsevell M., 2020. Europe's Green Deal offshore environmental damage to other nations. *Nature*, 586: 671-673.

Geels F.W., Sovacool B.K., Schwanen T., Sorrell S., 2017. Sociotechnical transitions for deep decarbonization. *Science*, 357(6357): 1242-1244.

Giannone D., Reichlin L., Sala L., 2006. VARs, common factors, and the empirical validation of equilibrium business cycle models. *Journal of Econometrics*, 132(1): 257-279.

Grimm S., Reiners W., Helwig N., Siddi M., Mourier L., 2021. *The Global Dimension of the European Green Deal: The EU as a Green Leader?* The Multinational Development Policy Dialogue, KAS, Brussels, Belgium, https://www.die-gdi.de/en/others-publications/article/the-global-dimension-of-the-european-green-deal-the-eu-as-a-green-leader/ (accessed on 3 November 2021).

Gütschow M., Feola G., 2022. Laying the foundations of a more conscious society? How vendors, consumers and organizers socially construct farmers' markets in Bogotá, Colombia. *Revista Colombiana de Ciencias Sociales*, 13(2): 455-476.

HLPE, 2017. *Nutrition and food systems*. A report by the High Level Panel of Experts on Food Security and Nutrition of the Committee on World Food Security, Rome.

Hurduzeu G., Pânzaru R.L., Medelete D.M., Ciobanu

A., Enea C., 2022. The Development of Sustainable Agriculture in EU Countries and the Potential Achievement of Sustainable Development Goals Specific Targets (SDG 2). *Sustainability*, 14(23): 15798.

IPES-Food, ETC Group, 2021. *A Long Food Movement: Transforming Food Systems by 2045*, https://www.ipes-food.org/_img/upload/files/LongFoodMovementEN.pdf.

Ivanov V., Kilian L., 2005. A practitioner's guide to lag order selection for VAR impulse response analysis. *Studies in Nonlinear Dynamics & Econometrics*, 9(1).

Jakada A.H., Mahmood S., Ahmad A.U., Garba Muhammad I., Aliyu Danmaraya I., Sani Yahaya N., 2022. Driving Forces of CO_2 Emissions Based on Impulse Response Function and Variance Decomposition: A Case of the Main African Countries. *Environmental Health Engineering and Management Journal*, 9(3): 223-232.

Jiakui C., Abbas J., Najam H., Liu J., Abbas J., 2023. Green technological innovation, green finance, and financial development and their role in green total factor productivity: Empirical insights from China. *Journal of Cleaner Production*, 382: 135131.

Joshi S., Singh R.K., Sharma M., 2023. Sustainable agri-food supply chain practices: Few empirical evidence from a developing economy. *Global Business Review*, 24(3): 451-474.

Kang S.H., Islam F., Tiwari A.K., 2019. 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. *Structural Change and Economic Dynamics*, 50: 90-101.

Karlsson S., 2013. Forecasting with Bayesian Vector Autoregressions. In: *Handbook of Economic Forecasting*, vol. 2, pp. 791-897. Amsterdam: Elsevier.

Kasztelan A., Nowak A., Hawlena J., 2019. *Green growth in agriculture in the European Union: myth or reality?*

Koop G., 2003. *Bayesian Econometrics*. Hoboken, NJ: Wiley.

Koop G., Pesaran M.H., Potter S.M., 1996. Impulse response analysis in nonlinear multivariate models. *Journal of econometrics*, 74(1): 119-147.

Kostornoi S., Yatsukh O., Tsap V., Demchenko I., Zakharova N., Klymenko M., Labenko O., Baranovska V., Daniel Z., Tomaszewska-Górecka W., 2021. Tax Burden of Agricultural Enterprises in Ukraine. *Agric. Eng*., 25: 157-169.

Kovalenko N., Hutsol T., Kovalenko V., Glowacki S., Kokovikhin S., Dubik V., Mudragel O., Kuboń M., Tomaszewska-Górecka W., 2021. Hydrogen production analysis: Prospects for Ukraine. *Agric. Eng*., 25: 99-114.

Kuboń M., Latawiec A.E., Scarano F.R., Drosik A., Strassburg B.B., Grzebieniowski W., Bastos J.G., 2019. Searching for solutions to the conflict over Europe's oldest forest. *Conserv. Biol*., 33: 476-479.

Kuokkanen A., Mikkilä M., Kuisma M., Kahiluoto H., Linnanen L., 2017. The need for policy to address the food system lock-in: A case study of the Finnish context. *Journal of Cleaner Production*, 140: 933-944.

Lanne M., Nyberg H., 2016. Generalized forecast error variance decomposition for linear and nonlinear multivariate models. *Oxford Bulletin of Economics and Statistics*, 78(4): 595-603.

Lillemets J., Fertő I., Viira A.H., 2022. The socioeconomic impacts of the CAP: Systematic literature review. *Land Use Policy*, 114: 105968.

Litterman R.B., 1986. Forecasting with Bayesian vector autoregressions—five years of experience. *Journal of Business & Economic Statistics*, 4(1): 25-38.

Mahy L., Dupeux B.E.T.I., Van Huylenbroeck G., Buysse J., 2015. Simulating farm level response to crop diversification policy. *Land Use Policy*, 45: 36-42.

Matthews H.D., 2016. Quantifying historical carbon and climate debts among nations. *Nature Climate Change*, 6(1): 60-64.

Muñoz-Villamizar A., Santos J., Grau P., Viles E., 2019. Trends and gaps for integrating lean and green management in the agri-food sector. *British Food Journal*, 121(5): 1140-1153.

Narayan P.K., Popp S., 2013. Size and power properties of structural break unit root tests. *Applied Economics*, 45(6): 721-728.

Niemiec M., Komorowska M., Szeląg-Sikora A., Sikora J., Kuboń M., Gródek-Szostak Z., Kapusta-Duch J., 2019. Risk assessment for social practices in small vegetable farms in Poland as a tool for the optimization of quality management systems. *Sustainability*, 11: 3913.

Notenbaert A., Groot J.C., Herrero M., Birnholz C., Paul B.K., Pfeifer C., Fraval S., Lannerstad M., McFadzean J.N., Dungait A.J., Morris J., Ran Y., Barron J., Tittonell P., 2020. Towards environmentally sound intensification pathways for dairy development in the Tanga region of Tanzania. *Regional Environmental Change*, 20: 1-14.

Nyangchak N., 2022. Emerging green industry toward net-zero economy: A systematic review. *Journal of Cleaner Production*, 134622.

Ogunniyi A.I., Omotoso S.O., Salman K.K., Omotayo A.O., Olagunju K.O., Aremu A.O., 2021. Socio-economic drivers of food security among rural households in Nigeria: Evidence from smallholder maize farmers. *Social Indicators Research*, 155: 583-599.

Ojo O.O., Shah S., Coutroubis A., Jiménez M.T., Ocana Y.M., 2018. *Potential impact of industry 4.0 in sustainable food supply chain environment*, 2018 IEEE International.

Oliver T.H., Boyd E., Balcombe K., Benton T.G., Bullock J.M., Donovan D., Feola G., Heard M., Mace G.M., Mortimer S.R., Nunes R.J., Pywell R.F., Zaum D., 2018. Overcoming undesirable resilience in the global food system. *Global Sustainability*, 1: e9.

Pesaran H.H., Shin Y., 1998. Generalized impulse response analysis in linear multivariate models. *Economics letters*, 58(1): 17-29.

Piet L., Desjeux Y., 2021. New perspectives on the distribution of farm incomes and the redistributive impact of CAP payments. *European Review of Agricultural Economics*, 48(2): 385-414.

Preiss M., Vogt J.H.M., Dreher C., Schreiner M., 2022. Trends Shaping Western European Agrifood Systems of the Future. *Sustainability*, 14(21): 13976.

Purcel A.A., 2020. New insights into the environmental Kuznets curve hypothesis in developing and transition economies: a literature survey. *Environmental Economics and Policy Studies*, 22: 585-631.

Qian J., Ruiz-Garcia L., Fan B., Villalba J.I.R., McCarthy U., Zhang B., Yu Q., Wu W., 2020. Food traceability system from governmental, corporate, and consumer perspectives in the European Union and China: A comparative review. *Trends in Food Science & Technology*, 99: 402-412.

Raimbekov Z., Syzdykbayeva B., Rakhmetulina A., Rakhmetulina Z., Abylaikhanova T., Ordabayeva M., Doltes L., 2023. The Impact of Agri-Food Supply Channels on the Efficiency and Links in Supply Chains. *Economies*, 11(8): 206.

Roser M., Ritchie H., 2019. *Hunger and undernourishment*. Our World in Data.

Sayadi-Gmada S., Rodríguez-Pleguezuelo C.R., Rojas-Serrano F., Parra-López C., Parra-Gómez S., García-García M.D.C., García-Collado R., Lorbach-Kelle M.B., Manrique-Gordillo T., 2019. Inorganic waste management in greenhouse agriculture in Almeria (SE Spain): Towards a circular system in intensive horticultural production. *Sustainability*, 11(14): 3782.

Sarantis N., Stewart C., 1995. Structural, VAR and BVAR models of exchange rate determination: a comparison of their forecasting performance. *Journal of Forecasting*, 14(3): 201-215.

Schaltegger S., 2018. Accounting for eco-efficiency. In: Id., *Green Accounting*, pp. 287-302. London: Routledge.

Schaltegger S., Sturm A., 1990. Okologische Rationalitat [Ecological Rationality]. *Die Unternehmung*, 4: 273-290.

Secundo G., Schena R., Russo A., Schiavone F., Shams R., 2022. The impact of digital technologies on the achievement of the Sustainable Development Goals: evidence from the agri-food sector. *Total Quality Management & Business Excellence*, 1-17.

Sihlobo W.; Kapuya T., 2021. *The EU's Green Deal: Opportunities, Threats and Risks for South African Agriculture*. 29 October 2021, https://theconversation.com/the-eus-green-deal-opportunities-threats-and-risks-for-south-african-agriculture-170811 (accessed on 14 November 2021).

Solazzo R., Pierangeli F., 2016. How does greening affect farm behaviour? Trade-off between commitments and sanctions in the Northern Italy. *Agricultural Systems*, 149: 88-98.

Tsioptsia K.A., Zafeiriou E., Niklis D., Sariannidis N., Zopounidis C., 2022. The Corporate Economic Performance of Environmentally Eligible Firms Nexus Climate Change: An Empirical Research in a Bayesian VAR Framework. *Energies*, 15(19): 7266.

Tubiello F.N., Karl K., Flammini A., Gütschow J., Obli-Laryea G., Conchedda G., Pan X., Yue Qi S., Halldórudóttir-Heiðarsdóttir H., Wanner N., Quadrelli R., Rocha Souza L., Benoit P., Hayek M., Sandalow D., Mencos Contreras E., Rosenzweig C., Rosero Moncayo J., Conforti P., Torero M., 2022. Pre-and post-production processes increasingly dominate greenhouse gas emissions from agri-food systems. *Earth System Science Data*, 14(4).

Tuscano M., Lamine C., Bre-Garnier M., 2021. Fostering responsible food consumption: A framework combining practice theories and pragmatism applied to an institutional experimental tool. *Journal of Rural Studies*, 86: 663-672.

United Nations Conference on Trade and Development, 2021. *A European Union Carbon Border Adjustment Mechanism: Implications for Developing Countries*, Geneva, Switzerland, https://unctad.org/webflyer/european-union-carbon-border-adjustment-mechanism-implications-developing-countries (accessed on 2 November 2021).

van Bers C., Delaney A., Eakin H., Cramer L., Purdon M., Oberlack C., Evans T., Pahl-Wostl C., Eriksen

S., Jones L., Korhonen-Kurki K., Vasileiou I., 2019. Advancing the research agenda on food systems governance and transformation. *Current Opinion in Environmental Sustainability*, 39: 94-102.

Wang G., Zhang Z., Li S., Shin C., 2023. Research on the influencing factors of sustainable supply chain development of agri-food products based on cross-border live-streaming e-commerce in China. *Foods*, 12(17): 3323.

Westhoek H.J., Overmars K.P., van Zeijts H., 2013. The provision of public goods by agriculture: Critical questions for effective and efficient policy making. *Environmental Science & Policy*, 32: 5-13.

Wolf S., Teitge J., Mielke J., Schütze F., Jaeger C., 2021. The European Green Deal—More Than Climate Neutrality. *Intereconomics*, 56: 99-107.

Yan H., Xiao W., Deng Q., Xiong S., 2022. Analysis of the Impact of US Trade Policy Uncertainty on China Based on Bayesian VAR Model. *Journal of Mathematics*, 2022.

Zafeiriou E., Azam M., 2017. CO_2 emissions and economic performance in EU agriculture: Some evidence from Mediterranean countries. *Ecological Indicators*, 81: 104-114.

Zafeiriou E., Azam M., Garefalakis A., 2022. Exploring environmental–economic performance linkages in EU agriculture: Evidence from a panel cointegration framework. *Management of Environmental Quality: An International Journal*, 34(2): 469-491.

Zafeiriou E., Karelakis C., Martínez-Zarzoso I., Galanopoulos K., Gkika D., 2023. Economic Development and Pesticide Use in EU Agriculture: A Nonlinear Panel Data Autoregressive Distributed Lag Approach. *Agriculture*, 13(9): 1693.