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Exploring the Dynamic Relationships between Agricultural Production and Environmental Pollution: Evidence from a GMM-SYS Model in the Three Seas Initiative (3SI)

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Abstract: The Three Seas Initiative (3SI) is still an under-researched area and is particularly important due to historical circumstances and economic backwardness. A study was carried out to assess the impact of renewable energy and production made by the agricultural sector on CO_2 emissions in 3SI countries between 2008 and 2020. The study used panel data analysis based on the two-step system's generalized method of moments (GMM) and the Dumitrescu–Hurlin panel causality test. The results show that a 1% increase in the value added generated by agriculture increased CO_2 emissions in the countries studied by 0.11%. In contrast, a 1% increase in GDP led to a 0.29% increase in CO_2 emissions. Conversely, when renewable energy consumption increased by 1%, CO_2 emissions fell by 0.25% in the countries studied. One way to reduce CO_2 emissions from agricultural production in the short term is to increase the share of renewables, which incidentally is in line with EU action.

Keywords: agricultural production; agriculture; GMM system; renewable energy; Three Seas Initiative

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Citation: Supron´, B.; Myszczyszyn, J. Exploring the Dynamic Relationships between Agricultural Production and Environmental Pollution: Evidence from a GMM-SYS Model in the Three Seas Initiative (3SI). *Sustainability* **2024**, *16*, 3748. https://doi.org/10.3390/su16093748

Academic Editor: Elena Cristina Rada

Received: 21 March 2024
Revised: 24 April 2024
Accepted: 26 April 2024
Published: 30 April 2024

1. Introduction

Climate change represents one of the most significant challenges currently facing the European and global economy today. In the context of ongoing change and geopolitical tensions, volatile energy and food prices have the potential to significantly impact global economic growth [1]. The concepts of energy, food production, agriculture and climate change are inextricably linked and must be considered together, particularly in the context of a globalized environment [2].

The global challenges of combating global warming while maintaining economic growth are prompting many countries to take joint initiatives. The Three Seas Initiative (3SI) is a platform for regional cooperation established in 2016 by representatives of 12 European Union member states: Austria, Bulgaria, Croatia, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia and Slovenia. The area encompassed by the 3SI accounts for almost one third of the total area of the European Union, and its population is more than 112 million people.

The 3SI is designed to facilitate deeper European integration and reinforce the cohesion of the EU, including through the development of communication infrastructure, the reinforcement of energy security and the promotion of the digital economy in Central Europe [3]. The 3SI member countries face a number of significant challenges, including the need to enhance energy security through the establishment of a robust and efficient energy market and to diversify their energy sources and suppliers [4].

The energy sector is a significant contributor to greenhouse gas emissions, including CO_2. Consequently, substantial investment is required to ensure climate protection and the implementation of sustainable development policies. Therefore, the choice between renewable and non-renewable energy sources has become a critical decision for all countries worldwide [5,6]. In turn, agricultural production is of paramount importance in ensuring food security. However, agricultural activities are also associated with the emission of significant quantities of N_2O and methane (CH_4) into the atmosphere [7,8].

There is a two-way relationship between the broader agricultural sector and climate [9]. On the one hand, agriculture is dependent on the presence of optimal climatic conditions (temperature, sunshine, precipitation and other aspects of climate that affect agricultural productivity). On the other hand, agricultural production is responsible for at least 9% of global greenhouse gas (GHC) emissions [10]. The primary sources of these emissions are gases from soil management practices, livestock production and the consumption of fossil fuels [11].

The adoption of rigorous standards by European Union countries to reduce greenhouse gas emissions by 2050 could present a significant challenge for the agricultural sector. However, the agricultural sector has the potential to emerge from the energy transition through participation in renewable energy generation and the utilization of low-carbon agricultural production techniques [12].

In light of the aforementioned considerations, the objective of this study was to assess the impact of renewable energy and production generated by the agricultural sector on CO_2 emissions in 3SI countries for the 2008–2020 period. The following research hypotheses were established for the study:

H1: *Agricultural production and economic growth both contribute to the release of CO_2 emissions in the short term in the Three Seas Initiative region.*

H2: *The utilization of renewable energy in 3SI countries is associated with a reduction in CO_2 emissions in the short term.*

To achieve the stated objective and verify the research hypotheses, the two-step system of the generalized method of moments (GMM) was proposed by Arellano and Bover [13] and Blundell and Bond [14], as this method provides consistent and robust results for short-term panel data. The two-step GMM procedure allows the results to be highly dependable, even in the presence of endogenous regressors. In addition, a causality analysis based on the Dumitrescu–Hurlin panel test was applied [15] to classify variables and select instruments in an appropriate manner.

The novel aspects of this study can be summarized as follows. First, this study analyzes the countries of the 3SI initiative, which is a new venture in Europe, and examines aspects of the group's functioning that have not been analyzed before. At the same time, this study is intended to stimulate discussion about this initiative and contribute to future research. Secondly, this study analyzes the links between agriculture and economic emissions for European countries, providing new evidence in this area. To date, the majority of the research on agriculture, energy and the environment has focused on countries in Asia and Africa. However, agriculture plays a significant role in European countries, and the challenges facing the sector in the context of the energy transition are an important political and economic issue.

Secondly, the model used in this study, the two-stage panel GMM, has an advantage over other approaches previously employed thus far in that it allows not only the study of causality but also the study of the absolute impact of factors in the short term. This represents a significant extension, as causality studies in the Granger sense alone do not necessarily provide information on the direction of the relationship. The GMM approach is further enhanced by identification of the interaction between agricultural activity and CO_2 emissions. Finally, to the best of our knowledge, no previous studies have considered the impact of renewable energy and agricultural production on CO_2 emissions in the Three Seas Initiative countries.

This article is structured in four sections. Following the introduction, a review of the literature is presented. Section 3 describes the variables in detail and the model specifications and gives a description of the econometric method. The empirical results and discussion are presented in Section 4. Finally, the conclusions and practical implications are presented in Section 5.

2. Literature Review

Over the past decade, researchers have increasingly focused on the relationship between pollution and broad economic categories. The scientific community's collective work is expected to contribute to the development of emission reduction strategies. The literature focuses on many aspects of the relationship between CO_2 emissions and human economic activity. Carbon dioxide has been identified in most studies as the main cause of global warming [16,17]. The global economic downturn that accompanied the pandemic period also provided new insights into the relationship between the economy and pollution. While the downturn was only for few months, it resulted in a significant decrease in greenhouse gas emissions worldwide. This suggests the importance of reducing fossil fuel consumption and reducing emissions in the economy. However, this decrease was only temporary, and the return to a state of normal economic activity resulted in a sharp increase in emissions [18].

The relationship between economic development and environmental degradation or quality can be broken down into three distinct effects: scale effects, composition effects and technical effects. As production increases, environmental pressures also increase, but these pressures can be counteracted by the other two effects [19,20]. The majority of studies use the environmental Kuznets curve (EKC), which illustrates the relationship between CO_2 emissions and economic growth [21].

The research on the EKC can be divided into two categories. The first category examines the causal relationships between economic development and environmental pollution, utilizing a high level of generalization due to the data aggregates [22]. The second aspect focuses on the relationship between economic parameters and energy consumption. It is widely acknowledged that greenhouse gas emissions are mainly caused by the economic use of natural resources, including fuels [23].

This area has been the subject of numerous works which have increasingly detailed analyses. They all share a focus on the EKC as the main cause of environmental degradation in various aspects of human activity. To date, the impact of macroeconomic determinants such as globalization on CO_2 emissions has been analyzed and determined by econometric methods [23], population growth [24], urbanization [25] and investment [26]. The last strand of research, based on global trends related to the energy transition, addresses the impact of renewable energy sources and sustainable production practices on environmental pollution [27]. Some researchers have combined economic growth, CO_2 emissions and the use of conventional and renewable energy sources [25,26,28,29].

Their findings indicate that in developing economies, there is a positive relationship between the GDP and CO_2 emissions [30]. In contrast, developed countries experience a negative impact from economic growth on pollution, as evidenced by the U-shaped EKC curve [31]. The utilization of contemporary econometric techniques, such as NARDL, has corroborated the nonlinear and asymmetric effects of economic growth and economic variables on CO_2 emissions [32,33]. The researchers have observed that technological advancement, educational attainment and globalization can serve to mitigate the adverse consequences of pollution resulting from economic development [34–36].

The majority of studies concur that non-renewable energy has a positive effect on the growth of emissions from human economic activity [28,37]. Researchers posit that ensuring both economic growth and adequate energy supplies lies in the deployment of renewable energy [27,38,39]. To gain a deeper understanding of the impact of renewable energy on CO_2 emissions, studies are continuously being conducted using updated data resources and modern econometric methods. However, contradictory results are often found, and specific conclusions depend on the region analyzed and the econometric method used [40].

Recent research has also examined the impact of individual industries on CO_2 emissions and the development of applied economic policies. Moreover, studies on the impact of agricultural activities on CO_2 emissions have also emerged. Global warming may have a negative impact on farm operations and agricultural production [41,42], while agriculture contributes to greenhouse gas emissions [43]. In light of the aforementioned considerations, the majority of studies conclude that there is bidirectional causality between agriculture and CO_2 emissions [34]. Jebli and Youssef [38], based on African countries, indicated that increased production in agriculture reduces CO_2 emissions in the long term. Conversely, using Pakistan as an example, Waheed et al. [9] indicated that an increase in agricultural production leads to an increase in CO_2 emissions. The relationship between agriculture and CO_2 emissions has been confirmed by numerous studies, including those conducted by Florea et al. [44] on CEE countries; Zafeiriou and Azam [45] on Mediterranean countries; Yan et al. [46] on European Union countries; and Jeremiás on large non-EU countries [47].

Furthermore, farming has been shown to influence soil degradation by increasing the surface area of agricultural land at the expense of forested areas and grasslands [48]. Mu et al. [49] indicated in the United States that there are bidirectional relationships between CO_2 emissions and agricultural land area [24]. Wu et al. [50] used China as an example to show that an increase in agricultural land area has a positive effect on the increase in GHC emissions. Similar conclusions were also obtained in studies on European countries [50].

Moreover, it is important to note that the majority of scientific studies identify potential for sustainable and low-carbon agriculture in terms of renewable energy sources [51]. Previous studies have shown that renewable energy has an impact on CO_2 reduction and has a positive impact on the volume of agricultural production [9,38,44]. Numerous studies also have found causal relationships between the agricultural sector's production volume and the share of renewable energy in total energy consumption. For instance, in Tunisia, bidirectional causal links have been observed between agricultural production volumes, renewable energy use and per capita carbon dioxide emissions [52]. Similarly, a sample of BRICS countries (Brazil, Russia, India, China and South Africa) found unidirectional causal links running from renewable energy to CO_2 emissions [53]. A multitude of research studies have demonstrated the significance of integrating renewable energy into agricultural practices. This integration is crucial for addressing environmental concerns, promoting sustainability and countering the effects of climate change [54].

Previous studies on the linkage between agricultural production, renewable energy and environmental pollution have used a wide range of panel econometric methods, including ARDL, the GMM and FMOLS [55]. However, an analysis of the literature reveals that comprehensive econometric studies in this area on European countries, including those in Central Europe, are still lacking. This study, therefore, contributes to the literature in three ways. Firstly, to the best of our knowledge, there have been no studies on the relationships between agricultural sector activities, renewable energy production, economic development and environmental pollution in 3SI countries. Secondly, this is the first study in which a two-stage system of the GMM is used for the identified countries. Thirdly, this study adopts a novel approach with instrumental variables and examines impacts in the short term.

Furthermore, the authors were motivated to examine the relationships between agricultural sector activities, renewable energy production, economic development and environmental pollution in 3SI countries due to the realization that some of these countries are among the top European countries with the worst air quality. At the same time, the agricultural sector occupies a unique economic and social position in these countries. Renewable energy, on the other hand, is still not widely used within the available possibilities. Therefore, it is essential to examine the factors discussed and present relevant conclusions and policy implications for the future.

3. Materials and Methods

The empirical study used data obtained from the World Bank's database (World Development Indicators) on the 13 countries comprising the Tri-Seas Initiative countries for the period of 2008–2020. The choice of the period was influenced by the availability of data and important events affecting CO_2 emissions in the surveyed countries. Firstly, in

2008–2009, there was a global financial crisis, which according to research had an impact on economic activity and CO_2 emissions [56]. Secondly, immediately after this time, there was a debt crisis in the eurozone, which also affected economic activity and thus environmental pollution. In 2015, the Paris Agreement was adopted, which redefined global climate policy. Finally, in 2019, the global pandemic of COVID-19 broke out, which again contributed to changes in CO_2 emissions due to the suspension of many economic and social activities [57].

The variables were selected based on previous research for other countries and regions [49,52,53,55]. A panel dataset encompassing both time series and cross-sectional data were used in the process of developing the model development process. This study used CO_2 emissions as the dependent variable, with economic growth, renewable energy consumption, agricultural land area, agricultural growth and value-added serving as explanatory variables. To ensure normal distribution and stability, the variables were log-transformed. The variables employed in the study, along with their respective sources, are presented in Table 1.

Table 1. Variables and sources.

Variables	Symbol	Measure	Dataset Source
Carbon dioxide emissions	CO_2	per capita metric tons	WDI
Agriculture value-added	AGDP	% of GDP	WDI
Gross domestic product	GDP	per capita USD constant (2015)	WDI
Renewable energy consumption	REW	% of total energy consumption	WDI
Agricultural land share	ALS	% of land area	WDI

Source: authors' research.

This study uses the GMM model developed by Arellano and Bover [13] and Blundell and Bond [14]. The choice of the GMM method was dictated by its robustness to endogeneity and heterogeneity. The model estimation framework uses lagged instrumental variables in the model for endogenous variables. The additional rationale for opting for the system GMM over ordinary least squares (OLS) lies in its ability to control bias and inconsistency, particularly the risk of omitting unobserved time-invariant country effects [58]. The system GMM offers a more reliable and effective estimation technique in regression models, which helps to ensure robustness by accounting for correlated errors between past and present observations. In our view, GMM estimations represent a more systematic and proficient approach compared with other GMM estimation methods [52].

Instruments are variables that are used to enhance parameter estimation in models, particularly in instances of endogeneity or other issues associated with an incomplete set of independent variables. Instruments are utilized to eliminate correlations between independent variables and model errors. Instruments can also be variables that are lagged in an appropriate manner. These instruments thus permit testing of the effect of the independent variables on the dependent variable.

The GMM model is particularly suited to the estimation of panel data, where the number of cross-sectional units is greater than the number of periods, and there are autocorrelation and heteroscedasticity issues. Based on both the theoretical and empirical evidence, it is not possible to apply panel data models with fixed effects or random effects when the aforementioned time series imperfections are present.

This study uses a systematic two-stage GMM model. The system GMM is more efficient and robust to heteroskedasticity and autocorrelation than the single-stage model [59]. A dynamic panel model utilizing a system GMM has an advantage over a difference GMM model in the case of random walk-type variables, which frequently occur when describing macroeconomic phenomena. Furthermore, orthogonal moment conditions are employed to counteract the situation where past levels convey little information about future changes. Consequently, the GMM-SYS technique, in conjunction with the transformation of forward orthogonal deviations instead of differentials, produces more efficient and precise estimates than the difference GMM method. Moreover, dynamic GMM solutions yield more accurate estimates than OLS models [60]. The general form of the model under study can be presented as follows:

$$CO_2 = f(GDP, AGDP, ALS, REW) \tag{1}$$

The following equation can be derived from the above:

$$CO_{2,\ it} = \alpha + \beta_1 GDP_{it} + \beta_2 AGDP_{it} + \beta_3 ALS_{it} + \beta_4 REW_{it} + \varepsilon_{\ it} \tag{2}$$

where α is the intercept, i and t represent the countries and time, respectively, β_1... and β_4 are the coefficients of the independent variables and ε is the error term.

After a logarithmic transformation to eliminate multicollinearity, the analytical form of the model was determined as follows:

$$lnCO_{2,it} = \alpha + \beta_1 lnGDP_{it} + \beta_2 lnAGDP_{it} + \beta_3 lnALS_{it} + \beta_4 lnREW_{it} + \varepsilon_{\ it} \tag{3}$$

A two-stage GMM system was used to analyze the relationships between the selected variables empirically. For the dynamic panel model using the system GMM, the analytical form of the model is as follows:

$$lnCO_{2\prime it} = \alpha + \Phi_1 lnCO_{2i,t-1} + \beta_1 lnGDP_{it} + \beta_2 lnAGDP_{it} + \beta_3 lnALS_{it} + \beta_4 lnREW_{it} + \eta_i + \lambda_t + \varepsilon_{i,t} \tag{4}$$

where α, β and Φ are the coefficients of the model, λ is the time-invariant country effect, η is an unobservable time effect, ε is a residual term and t is a time interval.

Subsequent to the estimation, verification was conducted through utilization of the Hansen test and the Diff-in-Hansen test, with the objective of ascertaining the robustness of the outcomes attained and the legitimacy of the instruments employed [61]. In addition, an Arellano–Bond test for serial correlation was also performed [62].

In order to guarantee the consistency and stability of the model, a robustness check was conducted in accordance with the methodology proposed by Bond and Windmeijer [63]. This check entails verifying that the estimated coefficient of the Φ of the lagged variable falls between the values obtained by estimating the pooled ordinary least squares (OLS) model as the upper bound and the fixed effect (FE) model as the lower bound. Furthermore, a control estimation of the random effects (RE) model and the Diff-GMM was also performed.

The objective of the present study is to estimate the model parameters and capture the causal relationships between variables. To achieve this objective, Dumitrescu and Hurlin's [15] causality test was used, which is appropriate for heterogeneous panel data models and based on Granger causality tests [64]. The Dumitrescu and Hurlin test assumes the null hypothesis of homogeneous non-causality and estimates the parameters using an individual Wald statistic. This statistic converges sequentially to a standard normal distribution and a semi-asymptotic distribution of the mean statistic, which is characterized for a fixed sample T. The results of the causality test for the GMM method can also be used to group the variables of the model appropriately in terms of their exogeneity and endogeneity [65].

4. Results and Discussion

Table 2 presents the summary descriptive statistics for the study variables. The dataset consisted of 237 observations of time series data from 2008–2020 for Tri-Seas Initiative countries. The descriptive statistics indicate that in the surveyed countries between 2008 and 2020, the average CO_2 emissions decreased, while the area of agricultural land and agricultural production in the GDP decreased concurrently. However, the GDP and the share of renewable energy consumption increased.

Table 2. Descriptive statistics.

Variables	CO_2		REW		AGDP		ALS		GDP	
	2008	**2020**	**2008**	**2020**	**2008**	**2020**	**2008**	**2020**	**2008**	**2020**
Mean	7.315	5.264	16.631	25.902	3.244	2.902	42.220	40.458	16,455.309	18,053.381
Min	3.723	3.564	7.630	14.760	1.342	1.086	21.392	23.042	6465.270	7963.310
Max	13.074	8.304	33.710	43.750	6.302	4.336	64.612	56.713	44,440.211	43,455.817
SD	2.734	1.399	8.492	9.325	1.395	1.020	13.515	10.317	9385.169	8239.371

Source: authors' research.

The correlation analysis is presented in Table 3. The correlation results revealed moderate correlations between the REW and ALS, between the AGDP and GDP and between the AGDP and CO_2. This result thus indicates that agricultural production has an impact on CO_2 emissions in the Triangle countries. Furthermore, there was a strong correlation between lnGDP and lnAGDP, indicating that when one variable increases, the other tends to decrease, and vice versa.

Table 3. Correlation matrix.

Variable	$\ln CO_2$	lnAGDP	lnALS	lnGDP	lnREW
$\ln CO_2$	1.000	−0.442	−0.139	0.420	−0.388
lnAGDP	−0.442	1.000	0.306	−0.798	−0.108
lnALS	−0.139	0.306	1.000	−0.291	−0.599
lnGDP	0.420	−0.798	−0.291	1.000	0.293
lnREW	−0.388	−0.108	−0.599	0.293	1.000

Source: authors' research.

In the initial phase of the study, the potential for endogeneity was assessed by determining the causal relationship between the study variables. For this purpose, a test based on the Dumitrescu–Hurlin panel data test was applied, the results of which are presented in Table 4. The results obtained indicate that there is bidirectional causality between the variables: $CO_2 \leftrightarrow$ GDP, $CO_2 \leftrightarrow$ ALS and REW $\leftrightarrow$ GDP. In contrast, unidirectional causality occurs between the variables $CO_2 \rightarrow$ AGDP, $CO_2 \rightarrow$ REW, ALS $\rightarrow$ GDP, GDP $\rightarrow$ AGDP, GDP $\rightarrow$ REW and ALS $\rightarrow$ REW.

To select an appropriate generalized method of moments model estimation, two models were estimated: OLS with fixed effects and pooled OLS. The results of both models are presented in Table 5, and an estimation of the random effects model was also carried out to confirm robustness. The F-test statistic for the fixed effects test was estimated to be 2.52 and was found to be statistically significant at the 1% level. This implies that the fixed effects were nonzero, thereby rejecting the pooled model in favor of the fixed effects model. Furthermore, the results of the Hausman test indicate that at the 1% significance level, the fixed effect model should be preferred over the random effect model in the estimation. Consequently, the fixed effects model was employed to assess the robustness of the GMM estimation results, and the error component was not correlated with the independent variables.

Table 4. Pairwise Dumitrescu–Hurlin panel causality tests.

Causality	W-Stat.	Zbar-Stat.	Prob.
GDP $\rightarrow CO_2$	3.558	3.563	0.000
$CO_2 \rightarrow$ GDP	2.511	1.920	0.055
ALS $\rightarrow CO_2$	2.404	1.753	0.080
$CO_2 \rightarrow$ ALS	2.807	2.386	0.017
AGDP $\rightarrow CO_2$	0.671	−0.964	0.335
$CO_2 \rightarrow$ AGDP	3.868	4.049	0.000
REW $\rightarrow CO_2$	1.274	−0.019	0.985
$CO_2 \rightarrow$ REW	2.483	1.877	0.061

Table 4. *Cont.*

Causality	W-Stat.	Zbar-Stat.	Prob.
ALS → GDP	7.891	10.354	0.000
GDP → ALS	2.030	1.168	0.243
AGDP → GDP	1.647	0.567	0.571
GDP → AGDP	2.900	2.531	0.011
REW → GDP	12.183	17.083	0.000
GDP → REW	3.109	2.859	0.004
AGDP → ALS	1.440	0.242	0.809
ALS → AGDP	2.076	1.239	0.215
REW → ALS	1.121	–0.258	0.796
ALS → REW	2.772	2.330	0.020
REW → AGDP	1.962	1.061	0.289
AGDP → REW	0.626	–1.034	0.301

Source: authors' research.

Table 5. Random and fixed effects OLS estimation (robustness check).

Variable	Fixed Effect		Random Effects		Pooled	
	Coeff.	**Prob.**	**Coeff.**	**Prob.**	**Coeff.**	**Prob.**
$CO_{2\,t-1}$	0.608	0.000	0.920	0.000	0.920	0.000
GDP	0.153	0.040	0.026	0.381	0.026	0.383
REW	–0.282	0.000	–0.036	0.042	–0.055	0.043
ALS	0.058	0.729	0.005	0.280	–0.036	0.282
AGDP	0.145	0.008	–0.055	0.867	0.005	0.867
Const.	–0.303	0.702	0.167	0.569	0.167	0.570
R2	0.826		0.958			0.958
Husman cross-section	24.570	0.02				

Source: authors' research.

The results obtained for the fixed effect model indicate that a 1% increase in the GDP was associated with a 0.15% increase in CO_2 emissions under this study. Conversely, a 1% increase in renewable energy consumption was associated with a 0.28% decrease in CO_2 emissions. The added value of agricultural production also had a significant impact on CO_2 emissions among the variables studied, with an increase of 1%, translating into a 0.14% increase in CO_2 emissions.

It should be noted, however, that ordinary OLS models are not without flaws and may fail to account for unobserved heterogeneity over time. Moreover, a significant proportion of economic panel data do not satisfy the underlying assumptions of the OLS method, including the absence of autocorrelation and heteroskedasticity. This can result in the generation of biased estimation results. Utilization of the GMM, however, offers a more consistent estimation approach.

To select an appropriate estimation method, according to Arellano and Bond (2001), it is necessary to compare the coefficient ϕ for the dependent variable ($CO_{2\,t-1}$) with the estimation results of the OLS models. When the Diff-GMM model's ϕ is equal to or less than that estimated by the fixed effects method, the GMM model estimation should be chosen as the systematic method. In light of the above, the final GMM was estimated using the two-step system method, and the results are presented in Table 6. Furthermore, to confirm the robustness of the results obtained, the Diff-GMM model is presented in the table.

The results indicate that a 1% increase in the value-added generated by agriculture was associated with a 0.11% increase in CO_2 emissions in the countries studied, under the assumption that all other variables remained constant. Given that a 1% increase in the GDP was associated with a 0.29% increase in CO_2 emissions, this result indicates that higher agricultural production has a more negligible impact on CO_2 emissions than other sectors of the economy. Moreover, the model obtained did not confirm that the change in agricultural land shares in the countries studied had a significant impact on CO_2 emissions in the short term. Moreover, these results are consistent with those obtained using the OLS method with the fixed effects and difference GMM methods, which further validates the robustness of the estimated model. Thus, the results obtained provide positive verification of hypothesis H1 and are comparable to those obtained in earlier studies by Dauda et al. [66] for African countries, by Waheed et al. [9] for Pakistan and by Doğan [67] for China.

Table 6. Two-step difference and system of generalized method of moments estimation.

Variable	System			Difference		
	Coeff.	Std. Err.	Prob.	Coeff.	Std. Err.	Prob.
$CO_{2\,t-1}$	0.678	0.182	0.006	0.453	0.201	0.042
GDP	0.297	0.070	0.004	0.261	0.113	0.038
REW	−0.247	0.155	0.097	−0.387	0.150	0.023
ALS	0.482	0.395	0.037	0.417	0.475	0.397
AGDP	0.107	0.096	0.149	0.208	0.116	0.097
Const.	−3.436	1.314	0.006			
AR (1)	0.092			0.078		
AR (2)	0.206			0.196		
Hansen p value	0.678	0.182	0.006	0.453	0.201	0.042
Sargan	0.297	0.070	0.004	0.261	0.113	0.038

Source: authors' research.

The results indicate that an increase in renewable energy consumption led to lower CO_2 emissions in the 3SI countries studied. For every 1% increase in renewable energy consumption, CO_2 emissions fell by 0.25%. Therefore, the results obtained demonstrate that reducing CO_2 emissions in a relatively short time involves increasing the share of renewables. Consequently, hypothesis H2 can be positively verified. These results are also consistent with those reported by Naseem and Guang Ji [52] for the SAARC countries and Liu et al. [53] for the BRICS countries.

In consideration of the diagnostic parameters of the model obtained, as evidenced by the Arellano–Bond autocorrelation test, it is notable that the null hypothesis of no first-order serial correlation in the first differences (AR (1)) was rejected. However, the null hypothesis of no higher-order serial correlation in the first differences (AR (2)) was not rejected. Consequently, the GMM estimator employed was deemed to be consistent.

The second type of test was the J Hansen test, which was used to ascertain whether the instruments used were exogenous and whether the resulting GMM-SYS model estimates were accurate. The results of the Sargan test of overidentification indicate that all the instruments were valid. In conclusion, the results of the Hansen test and the difference-in-Hansen test indicate that both the GMM instruments for the levels and the IV instruments were valid and significant for the outcome variable.

Considering the results obtained and the property of the data to confirm robustness, an estimation of the VAR model was carried out according to the method proposed by Abrigo and Lovem [68]. It was similarly estimated by using the first differences to remove the panel-specific fixed effects and to solve the orthogonality problem (Table A1). The two lags were selected based on three criteria: the Bayesian information criterion (MBIC), the Akaike information criterion (MAIC) and the Hannan and Quinn information criterion (MQIC). All variables were used as GMM-type instruments. The validity of the model was determined using the eigenvalue stability condition (Figure A1). Based on the model produced, a Granger causality test was calculated (Table A2). The results appear to confirm the observations made in the previous estimation with the two-stage GMM model. It seems that renewable energy, agricultural land area and economic growth may all have a causal effect on CO_2 emissions.

To visualize the impact of the studied factors on CO_2 emissions from agriculture, an impulse response function (IRF) was estimated using the Cholesky orthogonalization procedure and by estimating the standard errors and confidence intervals using a Monte Carlo simulation with 800 iterations (Figure 1). The results of the estimation show that there is a positive relationship between the GDP and agricultural area for CO_2 emissions. This relationship was particularly evident in the short term. In contrast, an increase in renewable energy consumption contributed to a decrease in carbon dioxide emissions.

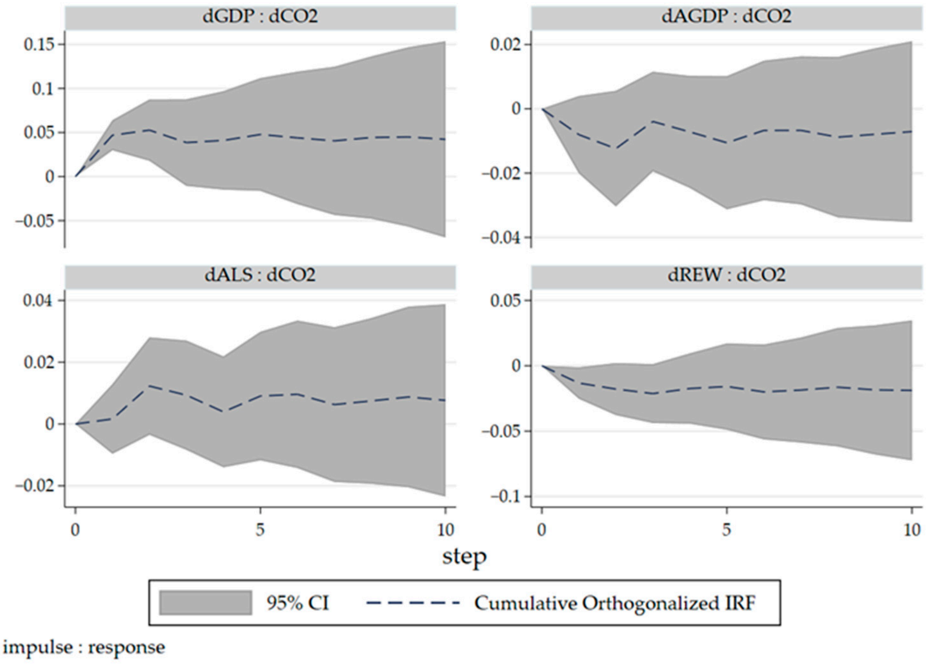

Figure 1. Impulse response functions for the PVAR GMM model. Source: authors' research.

5. Conclusions and Policy Implications

This study delved into the interplay among renewable energy consumption, economic growth, agricultural production, agricultural area and CO_2 emissions within the countries comprising the Three Seas Initiative from 2008 to 2020. Using both the OLS technique and the two-step system of the generalized method of moments, the findings indicate that an increase in the use of renewable energy sources is correlated with a reduction in carbon dioxide emissions. Conversely, economic growth and agricultural production are positively associated with CO_2 emissions in the countries examined. These results underscore the imperative to augment renewable energy adoption and diminish reliance on fossil fuels, thus making energy transition pivotal for fostering a sustainable economy and aligning with the Sustainable Development Goals.

This study advocates for agricultural and environmental policies in Three Seas Initiative countries to prioritize maintaining economic growth and agricultural production while curbing CO_2 emissions. This necessitates the establishment of robust, coordinated legal frameworks by individual governments to bolster air quality and foster long-term technological innovations. Collaborative efforts, including funding for research and development, cooperation among research centers and international research consortia, are recommended for creating and implementing low-carbon innovations in the agricultural sector.

It is imperative for 3SI governments to implement well-considered fiscal measures to incentivize low-carbon and renewable agriculture, transitioning toward efficient and sustainable production practices. This shift aims to meet escalating consumption demands while mitigating adverse environmental repercussions. Measures like introducing modern agrarian technologies based on renewable energy sources and enhancing farmer education are advocated for to enhance agricultural productivity and reduce emissions, including CO_2.

Furthermore, coordinated efforts among 3SI countries in developing renewable energy and leveraging the agricultural sector as a crucial component of the energy transition process are emphasized. Collaboration in renewable energy production and sales, the establishment of joint funds for renewable energy development and advocacy for increased financial support from entities like the European Union and the World Bank are recommended steps. In transitioning toward low-carbon agriculture, measures such as abandoning traditional farming techniques, reducing organic fertilizer and pesticide usage and stimulating investment and technological progress through international cooperation are vital. Policy interventions should aim to provide transitional protection for agricultural producers to mitigate adverse impacts on economic development amid the energy transition.

This study has limitations that can be addressed in future research. The focus is on the short-term relationship between economic growth, renewable energy, fertilizer consumption and CO_2 emissions from agriculture. Future studies could establish long-term relationships using modern estimation techniques such as ARDL and QARDL. The NARDL model could provide interesting evidence by examining the analyzed relationships asymmetrically. To use the indicated estimation techniques, longer time series would be required. Additionally, the set of variables was constrained by the objective of the study and the capabilities of the estimator. Given that the objective of this study was to identify the primary relationships, it might be beneficial to analyze other sets of variables using multivariate techniques for more detailed studies.

Future research could also consider other determinants, such as trade openness, financial development, foreign direct investment and organic farming. Further research could also utilize other gases emitted by agricultural activities, such as nitrous oxide or methane, as the dependent variable. Additionally, agricultural activities could be categorized into crop and livestock production. This type of research would complement the results obtained in this study, strengthening the scientific discussion on the energy transition of the agricultural sector.

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

Funding: This research was funded by the project within the framework of the Faculty of Economics of West Pomeranian University of Technology in Szczecin, Poland under the name "Green Lab. Research and Innovations".

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data upon which this article is based are supported by different data portals such as national government pages, repositories and other data sources.

Acknowledgments: The results of this work were presented at the 3rd International Conference Challenges and Opportunities for Rural Development (CORD 2023) on 29 November 2023 at the Warsaw University of Life Sciences in Poland.

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

Appendix A

Table A1. Main results of the PVAR model.

Independent Variables	Dependent Variables				
	ΔlnCO$_2$	**ΔlnREW**	**ΔlnAGDP**	**ΔlnALS**	**ΔlnGDP**
ΔlnCO$_2$(t − 1)	−0.432 ***	−0.272 **	0.572 ***	−0.009	0.026
	(0.093)	(0.086)	(0.119)	(0.015)	(0.031)
ΔlnCO$_2$(t − 2)	−0.507 ***	0.043	0.531 ***	−0.008	−0.028
	(0.092)	(0.077)	(0.131)	(0.019)	(0.030)
ΔlnREW(t − 1)	−0.040 *	−0.697 ***	0.316 **	0.010	0.012
	(0.068)	(0.079)	(0.096)	(0.015)	(0.030)

Table A1. *Cont.*

Independent Variables	Dependent Variables				
	ΔlnCO$_2$	ΔlnREW	ΔlnAGDP	ΔlnALS	ΔlnGDP
ΔlnREW(t − 2)	−0.129 * (0.083)	−0.431 *** (0.104)	0.462 *** (0.099)	−0.037 (0.023)	−0.105 *** (0.028)
ΔlnAGDP(t − 1)	−0.008 (0.036)	0.055 (0.053)	−0.707 *** (0.063)	0.002 (0.009)	0.003 (0.015)
ΔlnAGDP(t − 2)	−0.035 * (0.040)	0.086 (0.055)	−0.301 *** (0.070)	0.009 (0.007)	0.012 (0.016)
ΔlnALS(t − 1)	0.069 (0.167)	−0.474 (0.257)	−2.264 *** (0.367)	−0.657 *** (0.116)	0.089 (0.074)
ΔlnALS(t − 2)	0.301 * (0.139)	−0.092 (0.184)	−0.865 * (0.373)	−0.367 ** (0.135)	0.106 (0.064)
ΔlnGDP(t − 1)	2.063 *** (0.335)	−2.213 *** (0.390)	−4.187 *** (0.421)	0.157 * (0.068)	0.644 *** (0.131)
ΔlnGDP(t − 2)	−0.317 * (0.153)	−0.613 ** (0.222)	0.532 (0.274)	−0.052 (0.037)	−0.350 *** (0.055)

Notes: Δ is the first difference operator. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively. Source: authors' research.

Table A2. The results of the panel Granger causality test.

Dependent Variable	Independent Variables				
	ΔlnCO$_2$	ΔlnREW	ΔlnAGDP	ΔlnALS	ΔlnGDP
ΔlnCO$_2$		11.168 **	29.759 ***	0.406	2.312
ΔlnREW	2.463 *		23.116 ***	4.354	18.04 ***
ΔlnAGDP	0.930	2.429		2.293	0.614
ΔlnALS	5.575 *	3.711	40.4 ***		2.855
ΔlnGDP	41.772 ***	35.349 ***	99.789 ***	10.788 ***	

Notes: Δ is the first difference operator. ***, ** and * indicate statistical significance at 1%, 5% and 10% levels, respectively. Source: authors' research.

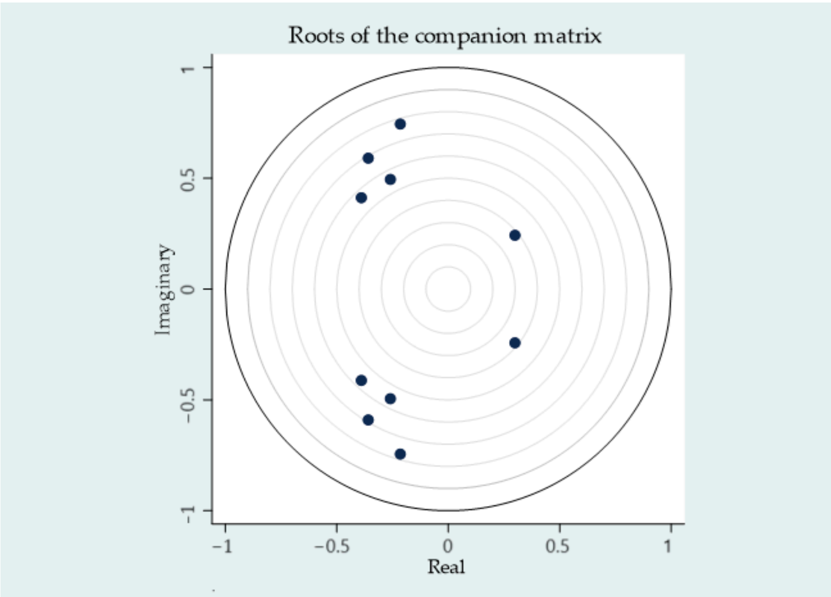

Figure A1. PVAR stability condition results and the unit circle results. Source: authors' research.

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