Research on World Agricultural Economy | Volume 07 | Issue 02 | June 2026

Research on World Agricultural Economy

https://journals.nasspublishing.com/index.php/rwae

ARTICLE

The Relationship Between Agricultural Carbon Dioxide Emission and Agriculture Subsectors Production: Static Panel Data Approach

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ABSTRACT

Human activities contribute to carbon dioxide (CO_2) emissions, which have serious environmental, economic, and social effects of climate change. This has sparked efforts to find large-scale solutions to eliminate the causes of climate change. While these solutions mainly involve reducing carbon emissions through global agreements, individual nations have also taken steps to cut emissions by changing production methods, such as irrigation and fertilisation, to ensure the efficient and effective use of resources and the proper storage and transportation of food. As a result, the agricultural sector is both a source and a victim of this process. The sector's environmental impact varies due to differing production techniques and energy needs across various sub-sectors like vegetable, grain, and fruit production. Increases in carbon dioxide emissions in this sector are connected not only to production activities but also to demographic and social factors, such as the rural population proportion. This study aims to explore the

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ARTICLE INFO

Received: 1 September 2025 | Revised: 20 November 2025 | Accepted: 25 November 2025 | Published Online: 28 May 2026
DOI: https://doi.org/10.36956/rwae.v7i2.2690

CITATION

Peker, A.E., Akdağ, N., Veysİkaranİ, D., et al., 2026. The Relationship Between Agricultural Carbon Dioxide Emission and Agriculture Subsectors Production: Static Panel Data Approach. Research on World Agricultural Economy. 7(2): 618–634.
DOI: https://doi.org/10.36956/rwae.v7i2.2690

effect of vegetable, grain, and fruit production, as well as the rural population ratio, on carbon dioxide emissions. To achieve this, a static panel data analysis was conducted across 21 European countries from 1970 to 2023. According to the research findings, vegetable production increases carbon emissions from agriculture. However, it was found to have a significant, albeit borderline, impact on fruit production and to reduce carbon emissions. These results demonstrate that agriculture's contribution to carbon dioxide emissions varies by sub-sector and provide valuable information for developing sustainable agricultural policies.

Keywords: Climate Change; Agriculture; Carbon Emissions; Europe; Panel Data Analysis; Economic Growth

1. Introduction

Global warming and climate change rank among the most pressing environmental challenges of the 21st century, primarily resulting from the rise in greenhouse gas emissions caused by human activities. The principal gases responsible for this increase include methane (CH_4), carbon dioxide (CO_2), and nitrous oxide (N_2O), which accumulate in the atmosphere, disrupt the Earth's energy balance, and contribute to long-term temperature increases. Rising temperatures have immediate implications for energy systems, particularly by reducing the efficiency of hydropower generation. In scenarios where alternative renewable sources, such as solar or wind energy, are unavailable, these conditions can precipitate energy shortages and crises. The consequences of climate change extend beyond environmental impacts, encompassing economic, social, and political dimensions. The Intergovernmental Panel on Climate Change (IPCC) emphasizes that reducing carbon emissions constitutes a fundamental requirement for attaining sustainable development goals and for implementing effective strategies to combat climate change[1].

The sectors most affected by, and drawing the most attention to, climate change today are energy, transportation and industry. However, agriculture also plays a significant role, with seemingly innocent practices that contribute to climate change through greenhouse gas emissions. Agricultural activities such as soil cultivation, the use of fertilizers and pesticides, irrigation systems, energy consumption and deforestation contribute to increased greenhouse gas emissions, both directly and indirectly. In this context, agriculture is not only considered an area exposed to the effects of climate change, but also a structural element that fuels this process. Data reported by the Food and Agriculture Organization (FAO) indicate that agriculture contributes an estimated 10–12% of total global greenhouse gas emissions[2]. These rates vary significantly depending on countries' production methods, levels of development, and technological infrastructure.

The agricultural sector itself is diverse, comprising various sub-sectors. The impact of agricultural output on the climate becomes even more complex when considering this structural diversity. Sub-sectors such as vegetable, grain, and fruit production show significant differences regarding farming techniques, energy and water requirements, mechanization levels, and input use. For instance, grain production generally involves extensive land use and heavy mechanization increasing fossil fuel consumption and carbon emissions[3]. Vegetable production, particularly greenhouse farming, is energy-intensive, whilst fruit cultivation can facilitate positive carbon sequestration under suitable conditions[4]. These structural differences make it essential and meaningful to evaluate the contributions of individual agricultural sub-sectors to carbon emissions separately.

In addition to the volume of agricultural production, the socio-demographic context in which it occurs also emerges as a key factor in assessing the climatic effects. Elements such as the prevalence of traditional farming practices, rural population percentages, technological adoption levels, and whether agriculture is for subsistence or commercial purposes influence production patterns. The ratio of rural to total population is particularly significant in shaping production structures and overall growth, especially in developing nations. High rural population ratios often support low technology levels, rely on intensive labour, and entail various sustainability risks[5, 6].

Consequently, conducting a multidimensional analysis of the various components of agricultural production and their impact on carbon dioxide emissions can provide critical insights for formulating policies that are consistent with sustainability objectives. The primary objective of this study is to examine the relationship between agricultural activities and their associated CO_2 emissions by analyzing the contributions of different components of the sector. Specifically, it examines the effects of variables such as vegetable, grain, and fruit production, as well as the rural population ratio, on agricultural carbon emissions. The study also evaluates how the structural diversity within agricultural production influences environmental outputs. Cross-country comparisons are performed using a panel data set, and the relationships are modelled with the Static Panel Data method, which accounts for heterogeneity across countries and common shocks. Employing the static panel data approach enhances the study's analytical robustness by addressing common methodological challenges. Consequently, this research provides not only empirical evidence of the agriculture-climate nexus but also establishes a solid methodological basis for informed policy making.

2. Theoretical Framework

The interaction between climate change and the agricultural sector is inherently dynamic and bidirectional, with each influencing and being influenced by the other. Although agriculture is one of the sectors most directly exposed to the adverse effects of climate change, it also plays a significant role in altering the climate system through its considerable greenhouse gas emissions[7]. Structural differences observed in the agricultural sector and production characteristics specific to sub-sectors significantly influence the level and form of environmental impacts. This two-way interaction necessitates a more in-depth examination of the environmental consequences of agricultural production patterns and production methods. In this context, analysing the effects of different components of agriculture on carbon emissions is of critical importance for the design of sustainability-focused agricultural policies.

2.1. The Role of Agricultural Sub-Sectors in Emissions

Agricultural production is not homogeneous in structure and contains significant diversity within itself. Sub-sectors such as vegetable, grain, and fruit production differ from each other in terms of both production technologies and input use. These structural differences lead to sectoral variations in the impact on carbon emissions. The relationship between agricultural sub-sectors and carbon emissions is shown in **Figure 1**.

Figure 1 illustrates the impact of agricultural subsectors on carbon emissions. Numerous factors influence this, from production to consumption. While these factors may increase or decrease production in the short term, they also affect environmental and economic sustainability in the long term.

- **Grain Production:** This form of agricultural production is typically conducted over extensive land areas and relies heavily on mechanization and intensive chemical inputs. Specifically, the intensive application of nitrogen-based fertilizers substantially increases emissions of carbon dioxide (CO_2) and nitrous oxide (N_2O), making this practice one of the leading sources of greenhouse gas emissions within agriculture[3].
- **Vegetable Production:** When carried out in covered (greenhouse) systems, vegetable production can contribute to increased carbon emissions due to high energy requirements. In addition, year-round irrigation, fertilisation, and pesticide applications are among the primary factors that contribute to the environmental burden of this production method[8].
- **Fruit production** has a contextually differentiated effect. The cultivation of certain fruit species in perennial and permanent tree forms can act as carbon sinks by sequestering atmospheric carbon in biomass and soil. However, in large-scale fruit plantations where intensive energy and water use are involved, this potential mitigating effect may weaken, contributing to net carbon emissions[4].

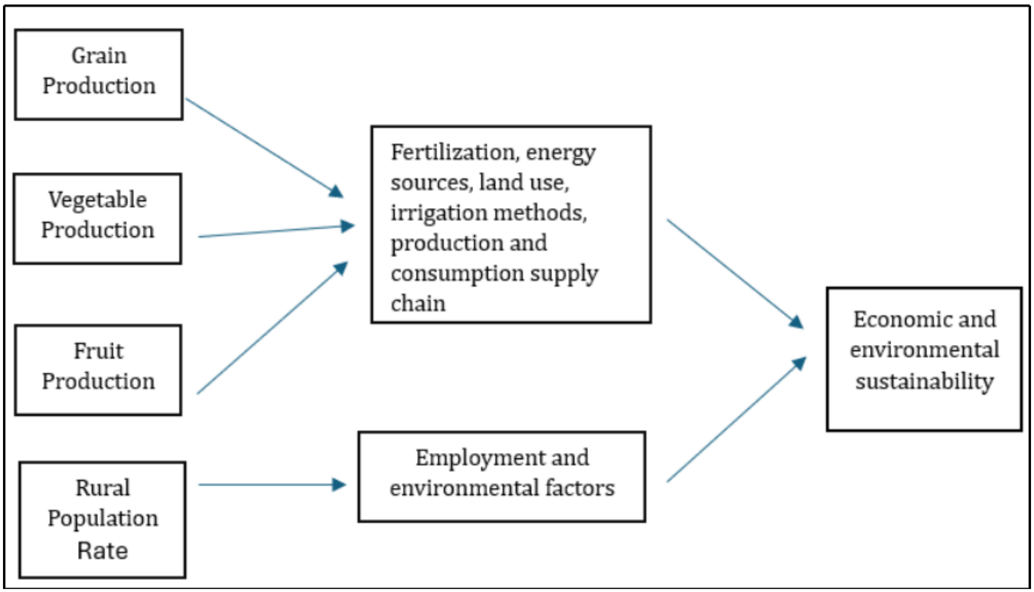

Figure 1. The relationship between agricultural subsectors and carbon emissions.

2.2. Rural Population and Agricultural Practices

The rural population ratio is considered an essential socio-demographic indicator that influences the form of agricultural production and the use of technology. In countries with a high rural population ratio, agricultural activities are typically carried out at a subsistence level, utilising low-tech and labour-intensive methods. While this production method may be limited in terms of direct energy consumption, it can create indirect environmental pressures due to factors such as inefficient land use, ineffective water use, and dependence on traditional energy sources[5]. On the other hand, in countries with low rural population ratios, agricultural activities are primarily organized in the form of industrial agriculture, which can increase fossil fuel use and result in enhanced emissions from agriculture[6].

2.3. Agriculture-Environment Interaction in the Context of Climate Change

The interaction between agricultural production and climate change must be assessed in a multidimensional manner within the framework of sustainability. According to reports published by the FAO[2] and the IPCC[1] the agricultural sector has the potential to both mitigate the effects of the climate crisis and exacerbate it. In this context, it is necessary to re-evaluate production patterns, promote low-carbon agricultural practices, and re-regulate agricultural policies with consideration for their environmental impacts.

In line with this theoretical framework, this study analyses the impact of vegetable, grain, and fruit production and the rural population ratio on carbon dioxide emissions from agriculture using the Static Panel Data approach, a static panel data method. The aim is to empirically reveal the extent to which the structural components of agriculture contribute to climate change, and to contribute to the shaping of environmentally friendly agricultural policies

3. Literature Review

Table 1 provides a systematic overview of the multidimensional relationship between agriculture, energy use, and CO_2 emissions.

Table 1. Literature review.

Author(s)	Country/Region	Method	Variables/Focus	Key Findings
Pant[9]	120 countries	Regression analysis	Agricultural inputs, energy use	Fertilizer and energy use increase CO_2, while irrigation and biomass use reduce it.

Table 1. *Cont.*

Author(s)	Country/Region	Method	Variables/Focus	Key Findings
Liu, Zhang & Bae [10]	ASEAN	Panel data	Agricultural value added, energy types	Renewable energy and agricultural value added reduce CO_2; non-renewable energy increases it.
Majewski et al. [11]	94 middle-income countries	Panel data	Renewable electricity, agricultural value added	1% increase in renewable electricity reduces CO_2 emissions by 0.18%.
Vleeshouwers & Verhagen [12]	EU	CESAR model	Soil carbon flux	Soil management practices are decisive for carbon sequestration.
Porter et al. [13]	Spain	Comparative analysis	Organic vs. conventional production systems	Organic farming produces 56% less emissions per area and 39% less per product.
Bayraç & Doğan [14]	Turkey	ARDL	Rainfall, temperature, CO_2, agricultural GDP	Rainfall and yield increases have positive effects; CO_2 and temperature increases have negative effects.
Hayaloğlu [15]	Global	Econometric analysis	Climate variables, CO_2	CO_2 and climate change negatively affect agricultural production.
Pakdemirl [16]	Turkey	Econometric analysis	CO_2, climate, economic growth	CO_2 and temperature increases reduce economic performance.
Doğan [17]	China	ARDL	Agriculture, CO_2, EKC	Agriculture increases CO_2 in the long term; Environmental Kuznets Curve (EKC) is confirmed.
Rafiq et al. [18]	53 countries	Panel data	Agriculture, trade openness	In high-income countries, agriculture and services reduce CO_2, while industry increases it.
Zaferiou & Axam [19]	Spain, France, Portugal	ARDL	Economic performance, CO_2	Short-term results of EKC hypothesis are reversed.
Chandio et al. [20]	Developing countries	ARDL, Johansen	Agriculture, temperature, rainfall, fertilizer, energy	Short- and long-term relationships between agricultural inputs and CO_2 are confirmed.
Haller [21]	European OECD	Spatial panel	Carbon footprint, agricultural chain	Economic growth increases carbon footprint.
Rokicki et al. [22]	EU	Panel data	Agricultural GHG, development	Emissions decrease in developing countries; remain stable in developed countries.
Okumuş [23]	Turkey	ARDL	Agricultural value added, energy, urbanization	Long-term relationships exist; energy and urbanization increase CO_2.
Dallı & Kütükçü [24]	Turkey	ARDL	Energy, growth, growth squared	Growth squared reduces CO_2; EKC is confirmed.
Ajam et al. [25]	Developed countries	Panel data	Agricultural value added, globalization	Both variables have an inverse relationship with CO_2.
Gafsi & Bakari [26]	37 Asia-Pacific countries	Panel data	Agricultural methane, exports, financial development	Methane emissions reduce growth, while exports and investment increase it.
Tagwi [27]	South Africa	ARDL	Agricultural growth, CO_2	Positive short-term, negative long-term relationship.
Zang et al. [28]	China	Time series	Trade, carbon intensity	Carbon intensity negatively affects long-term growth and trade.
Yang et al. [29]	China (Jilin)	Local analysis	Fertilizer use	Fertilizer use is a major source of CO_2 emissions.
Han et al. [30]	China	Decomposition analysis	Technological progress, agricultural development	Technological progress is decisive for CO_2.
Ben Jebli & Ben Youssef [31]	Brazil	Econometric analysis	Renewable energy, agricultural value added	Both reduce CO_2 emissions.
Li & Zheng [32]	China	Decomposition	Production, intensity, structural effect	Production and intensity increase emissions; structural effect reduces them.

Table 1. *Cont.*

Author(s)	Country/Region	Method	Variables/Focus	Key Findings
Luo et al. [33]	China	Decomposition	Agricultural production	Decomposition levels have different effects on CO_2.
Zhang et al. [34]	China (grain regions)	ARDL	Energy consumption, EKC	EKC is confirmed; agricultural energy reduces CO_2 in short and long term.
Hajimirzajan et al. [35]	Iran	Optimization-based model, supply chain management	Crop planning, climate advantages, water and land efficiency, farmer income security	Coordinated crop planning cut water use by 397 million m^3, reduced costs, and boosted productivity; further model improvements recommended.
Coderoni & Esposti [36]	Italy, 20 regions, 1951–2008	Long-term panel data	Agricultural production, productivity, GHG emissions	Agricultural production and productivity raise emissions; scale effects dominate, methane shows inverted-U pattern; active policies are key for reduction.
Shadkam & Irannezhad [37]	–	Simulation-based optimization, review	Agricultural supply chain, system performance, digital twin models, AI-based optimization	Simulation and optimization enhance supply chains and reduce waste; digital twin with reinforcement learning supports effective Agriculture 4.0 design.
Mirmozaffari et al. [38]	Iran, 22 cement companies, 2015–2019	DEA + Machine learning algorithms	Cement production, CO_2 emissions, energy efficiency, eco-efficiency	Additive DEA assessed efficiency; Malmquist index evaluated productivity; machine learning revealed hidden rules; single-model approach improved eco-efficiency.

In general, the literature examines in detail the effects of agricultural production, inputs, and applied methods on CO_2 emissions, revealing significant differences between different country groups and farming sub-sectors. These studies emphasize the necessity of infrastructure improvements, technological advancements, renewable energy use, and policy designs that take regional differences into account in order to reduce the environmental impacts of agriculture and make production sustainable. However, the existing literature has been limited in comprehensively modeling the multidimensional effects of agricultural production components on emissions and simultaneously considering cross-country heterogeneity and common shocks. In this context, studies that contribute both empirically and methodologically to the agriculture-CO_2 relationship can provide meaningful inputs for environmental sustainability and policy development processes.

4. Materials and Methods

The use of both time-series and cross-sectional observations to estimate economic relations is referred to as panel data analysis. This method is generally used when the number of cross-sectional data points (N) exceeds the number of periods (T), i.e., when $N > T$ [39].

Panel data analysis is quite advantageous because it is an analysis method that allows for the examination of both time and unit effects, rather than being limited to either one. Panels may be categorized according to their temporal scope as either short-term or long-term. When each unit contains the same number of observations, the dataset is considered a balanced panel; otherwise, if the number of observations varies across units, it is referred to as an unbalanced panel [40, 41]. Although there are many types of panels in the literature, the generally accepted panels can be listed as follows [42]:

1. Pooled Regression: If z_i contains only a constant term, then the ordinary least squares method provides consistent and efficient estimates for the common α and slope vector β.

$$Y_{it} = X'_{it}\beta + z_i^{'}\alpha + \varepsilon_{it} \tag{1}$$

2. Fixed Effects: If z_i cannot be observed but is related to X_{it}, the least squares estimator of β is biased and inconsistent due to the omitted variable. However, in this case, the model;

$$Y_{it} = \beta X'_{it} + \alpha_i + \varepsilon_{it} \tag{2}$$

Here, α_i = $z_i a$ includes all observable effects and represents a predictable conditional mean. In this context, the fixed effects approach treats, α_i as a group-specific fixed term in the regression model. The term "fixed" used here indicates that c_i is not stochastic, while also explaining the correlation between c_i and x_{it}.

3. Random Effects: When there is no correlation between independent variables and heterogeneous variables with unobservable unit effects, the model can be formulated as follows:

$$Y_{it} = \beta X'_{it} + E\left[z_i^{'}\alpha\right] + \{z_i^{'}\alpha - E\left[z_i^{'}\alpha\right]\} + \varepsilon_{it} \quad (3)$$

$$Y_{it} = \beta X'_{it} + \alpha + u_i + \varepsilon_{it} \quad (4)$$

The Hausman test is employed to determine the most suitable estimation approach in panel data analysis. Specifically, when a correlation exists between the unobserved individual-specific effects and the explanatory variables, the model with fixed effects is considered appropriate. Conversely, If correlation cannot be established, the analysis proceeds with the random-effects framework. The test essentially evaluates the difference between the within-group estimator, applied in the fixed effects framework, and the generalized least squares (GLS) estimator, used in the random effects approach, to guide model selection. After selecting the most effective estimator among these, tests are performed to detect deviations from the assumption in the model: heteroscedasticity for the problem of varying variance, autocorrelation for detecting temporal correlation in the error term, and cross- sectional dependence for detecting inter-unit correlation [42, 43]. If at least one of these deviations occurs, the variance-covariance matrix (Ω) of the error term is not equal to the identity matrix. In the final stage of the analysis, an appropriate robust error estimator is used to correct deviations from the assumption without touching the parameters, or appropriate estimation methods are used to solve the standard errors. In this study, standard error estimates were corrected using the Driscoll and Kraay method [44] according to the Driscoll-Kraay method, it has been shown that matrix estimators of the covariances of nonparametric time series can be developed to be robust for all forms of spatial and temporal correlation when N is constant and T is large. For the average series across cross-sections, a Newey-West-type correction is applied. The corrected error estimates make the covariance matrix consistent independently of the cross-section.

The use of both time-series and cross-sectional observations to estimate economic relations is referred to as panel data analysis, which allows for controlling unobserved heterogeneity across units and examining both temporal and cross-sectional effects (Baltagi [45]). Panels may be categorized as short-term or long-term, and as balanced or unbalanced depending on whether each unit contains the same number of observations (Hsiao [46]). Common panel estimators include pooled OLS, fixed effects, and random effects models, with the Hausman test employed to determine the most appropriate approach (Wooldridge [47]). In the present study, standard error estimates were corrected using the Driscoll and Kraay [44] method to account for potential heteroscedasticity, autocorrelation, and cross-sectional dependence. While dynamic panel methods, such as System GMM, are generally recommended when N $>$ T, T $\geq$ 3, and endogeneity or autocorrelation is a concern Thorpe & Leitao [48], in this study the number of cross-sectional units is smaller than the number of periods (N $<$ T), the dependent variable does not include a lagged term, and endogeneity tests indicated a low risk of endogeneity. Therefore, a static panel approach is both theoretically and empirically justified for the analysis, in line with prior methodological recommendations (Baltagi and Wooldridge [45, 47]).

5. Analysis Findings

This study aims to investigate the relationship between agricultural carbon dioxide emissions and the production of agricultural sub-sectors in selected countries in Europe between 1970 and 2023. To this end, panel data analysis was performed to examine the effects of independent variables on the dependent variable in terms of both units and time. The names, codes, sources, and descriptions of the series used in the study are detailed in **Table 2**.

The equation of the Driscoll-Kraay model is as follows:

$$\begin{gathered} AGCO = \beta_0 + \beta_1 lnVPRO_{it} + \beta_2 lnFPRO_{it} \\ + \beta_3 RURAL_{it} + \beta_4 lnCPRO_{it} + \mu_{it} \end{gathered} \quad (5)$$

Descriptive statistics are basic elements that provide information about dependent and independent variables prior to quantitative analysis. **Table 3** contains information about descriptive statistics.

Table 2. Description of Series Used in the Study.

Series Type	Serial Code	Series Name	The Source of the Series	Series Description
Dependent Variable	lnAGCO	Carbon dioxide (CO_2) emissions (total) excluding LULUCF (Mt CO_2e)	FAOSTAT	Percentage (%)
Independent Variable	lnFPRO	Fruit production (tons)	FAOSTAT	Logarithmic
Independent Variable	RURAL	Rural population (percentage of total population)	WORLD BANK	Percentage (%)
Independent Variable	lnCPRO	Grain production (tons)	FAOSTAT	Logarithmic
Independent Variable	lnVPRO	Vegetable production (tons)	FAOSTAT	Logarithmic

Table 3. Results of Panel Unit Root Tests.

Variable Name	Number of Observations	Average	Standard Deviation	Min.	Max.	Skewness	Kurtosis
lnAGCO	1134	0.747336	0.932676	0.000000	4.193400	1.479339	4.730146
lnFPRO	1134	13.88018	1.92496	9.803667	17.12781	−0.3360489	2.322033
RURAL	1134	30.694630	13.492810	1.811	68.260	0.321070	3.148937
lnCPRO	1134	15.685080	1.322611	12.969020	18.106970	−0.142020	1.797682
lnVPRO	1134	14.267270	1.380224	11.865940	17.120080	−0.085338	1.843723

Table 3 presents a total of 1134 observations utilized in the analysis. Additionally, it presents descriptive statistics for each variable, including the mean, standard deviation, minimum and maximum values, along with distributional measures such as skewness and kurtosis. Accordingly, the maximum value of the lnAGCO variable is (4.19) and the minimum value is (0), the maximum value of lnFPRO is (17.21) and the minimum value is (9.80), the maximum value of RURAL is (68.26) and the minimum value is (1.81), the maximum value of lnCPRO is (12.9) and the minimum value is (1.32), the maximum value of lnVPRO is (17.12) and the minimum value is (11.86).

Before proceeding with the panel regression analysis, it is essential to examine the stationarity properties of the variables. For this purpose, four commonly used panel unit root tests—Levin-Lin-Chu (LLC), Im-Pesaran-Shin (IPS), and Fisher-type ADF and PP tests—were employed. These tests help determine whether the series contains unit roots at their levels and ensure that the subsequent panel estimations are not affected by non-stationarity–related biases. The results of these tests are presented in **Table 4**.

Table 4. Results of Panel Unit Root Tests.

Variable	LLC (*p*)	IPS (*p*)	Fisher-ADF (*p*)	Fisher-PP (*p*)	Decision	Order
lncpro	0.0000	0.0000	0.0000	0.0000	Stationary	I(0)
lnfpro	0.0302	0.0000	0.0001	0.0000	Stationary	I(0)
lnvpro	0.0031	0.0168	0.5575	0.0586	Mostly Stationary	I(0)
d_population	0.0821	0.0001	0.0586	0.0000	Mostly Stationary	I(0)
d_lnAGCO	0.0000	0.0000	0.0000	0.0000	Stationary	I(0)

The results of the panel unit root tests are summarized in **Table 4**. In this regard, the Levin–Lin–Chu (LLC) and Im–Pesaran–Shin (IPS) tests, together with the Fisher-ADF and Fisher-PP statistics, consistently indicate that the variables do not exhibit a unit root at their level values. In particular, the *p*-values for the variables lncpro, lnfpro, and d_lnAGCO remain below the 0.05 significance threshold across all tests, clearly demonstrating that these series are stationary within the panel. Although one of the Fisher tests for lnvpro is not statistically significant, the stationarity implied by the LLC and IPS tests is supported, and the variable is therefore classified as "mostly stationary." Similarly, while the LLC test for d_population does not fully confirm stationarity, both the IPS and Fisher-PP tests indicate that the series is I(0). Taken together, the combined evidence from the four panel unit root tests suggests that all variables in the model are stationary at their level values (I(0)). This finding confirms that the subsequent panel regression analysis is unlikely to suffer from bias or inconsistency related to non-stationarity (Wooldridge and Pesaran[47, 49]).

In econometrics, specific preliminary tests must be carried out to select the appropriate model before the method can be determined. If the observations are homogeneous, i.e., if they do not have unit-specific and/or time-specific variations, the classical model is used. The F, LM, and score tests are employed to determine the appropriate choice between the classical and fixed effects models. When the model exhibits unit and/or time-specific effects, the fixed effects specification is preferred. In contrast, the likelihood ratio (LR) test is employed to determine between the classical and random effects models, with the random effects model being selected in the presence of unit and time effects. **Table 5** shows the estimation results for the classical, random effects, and fixed effects specifications.

Table 5. LM, F Score, and LR Test Prediction Results.

lnAGRO	**Fixed Effects Model (F Test)**		**Likelihood Ratio Model (LR Test)**		**Random Effects Model (LM Test)**	
	Coefficient	$p > \|t\|$	**Coefficient**	$p > \|t\|$	**Coefficient**	$p > \|t\|$
lnFPRO	−0.0301	0.276	−0.0271	0.316	−0.0268	0.322
lnCRPO	−0.0841	0.019	−0.0587	0.092	−0.0552	0.105
RURAL	0.0046	0.011	0.0047	0.009	0.0047	0.008
lnVPRO	0.3691	0.000	0.3849	0.000	0.3868	0.000
_cons	−3.8556	0.000	−4.2415	0.000	−4.2901	0.000
R^2	0.0847 (Within)		0.3707 (Overall)			
F	Prob > F=0.0000		Prob > chi2 = 0.0000		Prob > F = 0.0000	
Score Test	Sigma_u = 0 chi2(1) = 6.5e + 0		Prob > chi2 = 0.0000			

Table 5 reports the results of the F, LM, and LR tests, which were conducted to assess the presence of individual (unit) and/or time effects in the panel data model. The F-test examines whether the combined individual effects are equal to zero under the null hypothesis. According to the test results, the null hypothesis is rejected at a 5% significance threshold ($p < 0.05$), indicating that the classical pooled model is not appropriate. Subsequently, the LM and Score (Breusch-Pagan) tests are applied to determine whether the random effects model should be preferred over the pooled model. According to the test result, the probability is less than 0.05, so the null hypothesis is rejected. It has been observed that the classical model is not appropriate and that there are unit and time effects. The LR test is used to determine whether to select between the fixed effects model and the classical model. According to the test result, the probability is less than 0.05, so the null hypothesis is rejected. The presence of unit effects was detected in all three tests. The Hausman test is applied to assess whether the hidden effects specific to each unit have a relationship with the explanatory variables. If such a correlation exists, the fixed effects model is considered the appropriate specification; otherwise, the random effects model is preferred. The outcomes of the Hausman test, which guide this model selection, are reported in **Table 6**.

The primary null hypothesis in the Hausman test states that the random-effects estimator maintains both consistency and efficiency. Conversely, the alternative hypothesis indicates that while the fixed-effects estimator remains consistent, the random-effects estimator fails to be consistent and is therefore invalid. The p-value obtained from the Hausman test being below 0.05 leads to the rejection of the null hypothesis. This outcome implies that the fixed effects model provides consistent and efficient estimates. Accordingly, the fixed effects specification is presented in **Table 7**.

To reinforce the credibility and robustness of the findings, supplementary diagnostic tests for autocorrelation, heteroskedasticity, and cross-sectional dependence were performed to detect any potential violations of the model's underlying assumptions.

Table 6. Hausman Test.

Hausman Specification Test Results
Null Hypothesis (H_0): $H_0 = E(x_{it},\ \mu_i \neq 0)$ Test Statistic: chi2(4) = (b−B)'[(V_b−V_B)^(−1)](b−B) = 13.64 Prob > chi2 = 0.0085*

*The null hypothesis is rejected at the 1% significance level.

Table 7. Fixed Effects Model and Deviation from Assumption Test.

AGRO	**Coefficient**	**Robust Standard Error**	$p > \|Z\|$	**95% Confidence Intervals**	**Multiple Linear Regression VIF Value**
lnFPRO	−0.0301	0.0276	0.276	[−0.0841, 0.0240]	4.17
lnCPRO	−0.0841	0.0358	0.019	[−0.1542, −0.0139]	4.87
RURAL	0.0046	0.0018	0.011	[0.0010, 0.0082]	2.36
lnVPRO	0.3691	0.0420	0.000	[0.2868, 0.4515]	1.31
_cons	−3.8556	0.6176	0.000	[−5.0674, −2.6438]	3.68 (Mean)

F(20,1109) = 25.64 prob > F = 0.0000
R^2 = 0.0847 (Within)
Number of Observations = 1134, Number of Groups = 21
Heteroscedasticity
Modified Wald test for groupwise heteroskedasticity in fixed effect regression model
H0. $\sigma(i)^2 = \sigma^2$ *for all i*
chi2 (21) = 523007.69
Prob > chi2 = 0.0000
Autocorrelation
Bhargava, Franzini, and Narendranatha's Durbin Watson Test 0.24275306
Baltagi-Wu LBI 0.2787904
Inter-unit Correlation
Pesaran CD Test 14.914, Pr = 0.0000
Friedman's Test 198.108, Pr = 0.0000
Frees Test 3.817, Pr = 0.0000

The fixed effects model employed in this study exhibits a two-way panel structure, allowing for the control of both unit-specific and time-specific effects. To identify potential deviations from the assumption of homogeneity of variances, the Levene, Brown, and Forsythe tests were conducted. These tests are based on the null hypothesis that the variances across units are equal. The test results indicate that the chi-square statistics (df = 20, 1113) and associated *p*-values are below 0.05, leading to the rejection of the null hypothesis and confirming that the model residuals are heteroskedastic.

The assumption of no serial dependence in the error terms was evaluated using the Durbin-Watson and Baltagi-Wu LBI tests. For both tests, the test statistics exceeded the threshold value of 2, indicating that the null hypothesis of no serial dependence could not be rejected. Therefore, the residuals do not exhibit significant temporal correlation, which supports the reliability of the parameter estimates. To assess potential correlation among residuals across cross-sectional units, the Frees test, Pesaran CD test, and Friedman test were applied. Both the Pesaran CD and Friedman tests are based on the null hypothesis of no cross-sectional correlation. The results show that the Pesaran CD test yielded a *p*-value below 0.05, leading to the rejection of the null hypothesis and indicating the presence of inter-unit correlation. Similarly, the Friedman and Frees tests also returned *p*-values below 0.05, further confirming cross-sectional dependence. This suggests that shocks affecting one unit may also impact other units, which is an important consideration for the estimation of standard errors and proper model specification.

The potential for multicollinearity among the independent variables was evaluated using the Variance Inflation Factor (VIF) test. The VIF measures the extent to which the variance of a regression coefficient is inflated due to linear dependence among explanatory variables. Generally, VIF values below 5 indicate negligible multicollinearity, values between 5 and 10 indicate moderate risk, and values above 10 indicate serious multicollinearity[50–52]. In this study, all individual VIF values as well as the average VIF were below 5, indicating that multicollinearity is not a concern. This ensures that the estimated coefficients are stable and not distorted by correlations among the explanatory variables.

Overall, while heteroskedasticity and cross-sectional dependence were detected, serial correlation and multicollinearity were not significant concerns. Therefore, standard error estimates were corrected using the Driscoll and Kraay[44] method, which provides reliable results accounting for heteroskedasticity, serial correlation, and cross-sectional dependence. This approach ensures that inferences based on the regression coefficients remain valid, even in the presence of deviations from classical assumptions.

According to the assumption deviation test, there is a correlation and autocorrelation problem between units. The Driscoll-Kraay standard error estimator is used to correct these deviations. **Table 8** presents the results of the Driscoll-Kraay standard error estimator.

Table 8. Driscoll-Kraay Standard Error Estimator Results.

Fixed Effects Model				**Number of Observations = 1134** **Number of Groups = 21**		
F(21, 1134) = 24.98 Prob > F = 0.0000				$R^2 = 0.0847$ (within)		
	Coefficient	**Standard Error**	***T***	***p***	**Confidence Intervals 95%**	
lnFPRO	−0.0301	0.0150	−2.00	0.050*	−0.0601	0.0000
RURAL	−0.0841	0.0633	−1.33	0.190	−0.2110	0.0428
lnCPRO	0.0046	0.0024	1.96	0.055	−0.0001	0.0094
lnVPRO	0.3691	0.0491	7.52	0.000*	0.2707	0.4676
Sabit	−3.8556	0.8661	−4.45	0.000*	−5.5928	−2.1184

Note: *, **, and *** denote statistical significance at the 5%, 1%, and 0.1% levels, respectively.

According to **Table 8**, the Driscoll-Kraay standard error estimator has 1134 observations and 21 groups. The F-test p-value is less than 0.05, that is statistically significant. Based on the R^2 result, the independent variables explain 0.08% of the dependent variable when other conditions are held constant. The remaining 92% indicates that other variables are explanatory. Among the independent variables used in the model, lnFPRO, and lnVPRO are significant at the 5%, as their p-values fall below 0.05 According to the model's coefficient interpretations, each a %1 increase in fruit production (lnFPRO) decrases carbon dioxide (CO_2) emissions from agriculture (lnAGRO) by 0.030%. Each 1% increase in vegetable production (lnVPRO) increases lnAGRO by 0.369%. The constant variable is significant in the model because its probability value is less than 0.05, but its coefficient sign is negative.

6. Discussion

Grain, fruit, and vegetable sectors constitute the fundamental components of agricultural and food production. However, when examined in terms of their environmental impacts, particularly carbon emissions, significant differences emerge among these sectors. The contrasting effects of fruit and vegetable production on agricultural emissions found in the model results align closely with broader patterns in the literature. A large body of empirical research emphasizes that input intensity, soil management practices, and technological characteristics of production systems are key determinants of agricultural emissions. For example, Porter et al.[13]

show that organic farming generates 56% fewer emissions per hectare due to reduced chemical input use—supporting the model's finding that vegetable production, which requires large amounts of nitrogen fertilizers, has an emission-increasing effect. Similarly, Yang et al.[29] and Chandio et al.[20] identify nitrogen fertilizer use as a major driver of CO_2 and N_2O emissions, confirming that input-intensive sectors such as vegetable production tend to raise overall agricultural emissions.

Conversely, the perennial structure and carbon sink capacity of fruit orchards are consistent with findings in the literature regarding soil carbon dynamics, biomass accumulation, and long-term carbon storage. Vleeshouwers and Verhagen[12] stress that soil carbon flux is highly sensitive to management practices, and that perennial systems enhance long-term soil carbon sequestration. Decomposition-based studies such as Luo et al.[33] and Li & Zheng[32] similarly highlight that structural shifts—such as moving from annual to perennial systems—have emission-reducing effects. Thus, the model's result showing that increased fruit production lowers net emissions is well aligned with the literature on the carbon sequestration potential of perennial agricultural systems.

Moreover, studies such as Haller[21] and Rokicki et al.[22] show that the relationship between agricultural development and emissions depends heavily on the production structure. Fruit production, which is less input-intensive and possesses long-term carbon storage capacity, can contribute to agricultural growth without proportionately increasing emissions. In contrast, the input-heavy nature of vegetable production—combined with factors such as fertilizer use, energy consumption, urbanization and industrialization emphasized in studies like Bayraç & Doğan[14] and Okumuş[23]—helps explain the emission-increasing response observed in the model.

Overall, both the model results and the broader literature converge on the conclusion that perennial fruit production plays a strategic role in reducing agricultural emissions, whereas annual, input-intensive vegetable production tends to increase them. This convergence reinforces the importance of crop-specific differentiation and the promotion of perennial systems as part of sustainable agriculture and climate mitigation strategies.

A similar study examining greenhouse gas emissions from different fruit types (e.g., fresh fruits, pears, apricots, etc.) also found that fruit production results in higher emissions compared with vegetable or grain production[53, 54]. Another study analyzing the energy efficiency and greenhouse gas emissions of date production in Adıyaman concluded that fruit production generates a significant carbon footprint[55]. The majority of carbon emissions originating from fruit production are associated with fertilization, irrigation, and pest control. For example, in an intensive apple-production study, pesticide manufacturing and application accounted for approximately 51% of total greenhouse gas emissions, a rate lower than in citrus and sugar beet production[56, 57]. Furthermore, a life-cycle-based study conducted in China revealed that 54.4% of emissions in apple orchards stem from fertilizers and 30.9% from electricity used for irrigation[56]. These findings align with the results of Pant[9] and Chandio et al.[20], which demonstrate that fertilizer and energy use are key determinants of agricultural CO_2 emissions[57, 58].

Several factors explain the high carbon emissions associated with fruit production. First, fruit trees are typically long-lived crops, and their management involves energy-intensive practices such as fertilization, irrigation, and pesticide application. In addition, fossil-fuel consumption by agricultural machinery used in fruit cultivation further contributes to emissions[52]. The literature also supports these findings: Han et al.[30] identified agricultural development level, the intensity of modern techniques, and input quantity as major drivers of CO_2 emissions, while Yang et al.[29] showed that fertilizer use in particular constitutes the primary source of agricultural CO_2 emissions[59, 60]. Moreover, the transportation stage of fruit production also has a substantial carbon footprint; long-distance transport in particular relies heavily on fossil fuels, thereby increasing emissions. Haller[21] supports this conclusion by demonstrating that geographical and economic dynamics within agricultural supply chains shape carbon footprints, with long-distance transportation significantly raising emissions[60]. In addition, because fruit production is largely carried out using modern agricultural techniques, the high greenhouse gas emissions associated with these techniques are well-documented.

Grain and vegetable production, on the other hand, generally generate lower levels of carbon emissions. The main reason is that grain production typically involves shorter growing periods and requires less energy for plant development. Vegetable production also tends to consume less energy in transportation, as vegetables can be grown in diverse climates and closer to consumption centers. Numerous studies in the literature emphasize that fruit production creates higher carbon emissions compared with other agricultural activities and highlight the need for measures to mitigate the sector's environmental impacts [51, 53]. In this context, Zhang et al. [34] found that energy consumption in major grain-producing regions reduces emissions in both the short and long run, indicating that the grain and vegetable sectors have relatively lower carbon profiles [55].

7. Conclusions

Carbon emissions are an important issue in agricultural production processes and are a complex phenomenon influenced by many factors. The levels of carbon emissions in grain, fruit, and vegetable production generally vary depending on many factors such as agricultural practices, energy use, agricultural land management, and climatic conditions. Here are some scientific discussions on why vegetable production may result in higher carbon emissions compared to other agricultural products:

Chemical Fertilizers and Pesticides: Pesticides and chemical fertilizers used in fruit and vegetable production cause various damages to the environment. In particular, they reduce soil fertility, lower fruit quality, and decrease population diversity. They also pass to humans through food. This situation highlights the importance of natural fertilization methods [55].

Energy Intensity: Studies conducted in recent years have shown that, in addition to human destruction, the amount of energy used in fruit and vegetable production is one of the factors contributing to the spread of carbon dioxide emissions. The rate is striking at 32% [56].

Land Use and Changes: Soil is of great importance in fruit production. In addition to combatting climate change, countries with large populations should prioritise producing and consuming low-carbon fruit, specialize in land use for agriculture, and implement marketing incentives that reduce carbon consumption [56, 57].

Logistics and Transportation: Fruits generally have a short shelf life. In some countries, access to fruits is limited due to climatic conditions. Therefore, logistics and transportation are of great importance. In this context, although cold transportation methods are preferred and fruits are stored under appropriate conditions to extend their shelf life, this increases carbon emissions. Using short-distance cold transportation methods can reduce carbon emissions [58, 59].

Irrigation Water Surfaces: Water usage is of great importance in fruit production. The efficient use of water without wastage, increasing energy efficiency to reduce carbon emissions, and utilizing water transportation and fertilization systems are crucial [60].

Climate Change Impacts: Climate change is one of the most significant factors affecting both fruit production and carbon emissions. In this context, a wide range of measures can be taken to produce different fruits adapted to climate change, improve soil drainage, and reduce carbon emissions [61].

In general terms, there are many factors that affect the carbon emissions associated with fruit production, from production to consumption. The most influential factors among these are listed above. For this reason, since it is not possible to undertake a mission to reduce fruit production, efforts have been increased to find answers to the question of how production can be carried out with lower carbon emissions. However, prior to this, the research question of whether there is a strong relationship between fruit production and carbon emissions, or the degree of this relationship, has been the focus of this study. Unlike other studies, this study has revealed a positive and strong relationship between fruit production and carbon emissions. When the findings of the study are evaluated, the adoption of sustainable agricultural practices is of great importance. In this context, increasing energy efficiency in agricultural production, developing alternative methods such as the use of organic fertilizers, and improving ecosystem management can contribute to reducing emissions. Liu et al.[62], Wróbel-Jędrzejewska and Przybysz[63], and Sharma et al.[64] support the findings of the study and suggest effective methods such as improving storage conditions to ensure a long shelf life and adopting appropriate production methods to prevent carbon emissions from fruit production[62–64]. In the future, the implementation of such strategies will minimize the environmental impacts of agricultural production.

Author Contributions

All authors contributed equally to the conception, design, data collection, analysis, and writing of this study. All authors have read and agreed to the published version of the manuscript.

Funding

This work received no external funding.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The data used in this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

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