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# AGRI-ENVIRONMENTAL INDICATORS IN THE EU: MEASURING DISCREPANCIES ACROSS MEMBER STATES

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## ABSTRACT

The paper analyzes agri-environmental indicators of EU countries from 2017 to 2023 to assess progress toward sustainable agriculture. Using descriptive statistics, principal component analysis (PCA), and a composite index, it identifies key sustainability dimensions and ranks EU countries by performance. Results indicate reduced agricultural greenhouse gas emissions, growth in renewable energy production, and expansion of organic farming areas. However, pesticide sales and related environmental risks remain high, highlighting ongoing dependence on chemical inputs. PCA reveals two main components: the first reflects energy and agricultural sustainability, while the second captures ecological risks linked to pesticide use and emissions. The composite index shows clear disparities among EU countries—some have advanced, while others lag behind the EU average. Findings suggest that EU agricultural policy should intensify pesticide reduction efforts while continuing to promote renewable energy and organic farming initiatives.

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## Introduction

Agriculture in the European Union (EU) plays a key role in achieving the goals of sustainable development, but at the same time represents a significant source of pressure on the environment through greenhouse gas emissions, energy consumption, soil degradation and intensive use of pesticides (Eurostat, 2023). That is why specific agri-environmental indicators (AEIs) were developed as an instrument for monitoring the relationship between agriculture and the environment, and which enable the assessment of progress towards sustainable production patterns (OECD, 2025; European Commission, 2025).

The development and implementation of AEIs has a dual significance. On the one hand, they enable the adoption of informed policies within the Common Agricultural Policy (CAP), while on the other they provide a basis for international comparisons and the identification of disparities among member states (Rega et al., 2020). Previous research has shown that despite progress in increasing the share of renewable energy sources and the expansion of areas under organic agriculture, the EU still records a high level of dependence on pesticides and a relatively slow reduction of greenhouse gas emissions from agriculture (European Environment Agency, 2023).

It is especially important to observe the temporal dynamics and compare different EU countries, because there are pronounced differences in the intensity of agriculture, the degree of implementation of sustainable practices and national environmental protection policies (Latruffe et al., 2016; Mihajlović et al., 2025; Dimitrijević, 2025). Analytical approaches such as Principal Component Analysis (PCA) and the calculation of composite indices are increasingly used in the scientific literature in order to turn the unified indicators into measurable dimensions and to perform the ranking of countries, which provides clearer insights into the structure and dynamics of the observed parameters (Angilella et al., 2018).

Starting from these assumptions, the goal of this work is to, using a set of agri-environmental indicators, perform a comparative analysis of EU member states for 2017 and 2023, with a focus on identifying the main dimensions of environmental indicators in agriculture. This approach enables a better understanding of the extent to which member states have progressed in the transition to sustainable agriculture and where the key challenges for future development lie. The main goal of this work is to carry out a comprehensive analysis of agri-environmental indicators in the countries of the European Union in 2017 vs. 2023, with an emphasis on the identification of disparities among member states and the ranking of countries according to overall performance.

## Literature review

Agriculture is increasingly viewed as a sector that, in addition to its economic role in food supply, must also contribute to the preservation of the ecosystem and the reduction of the ecological footprint. Numerous studies indicate that sustainable practices, such as organic production and the reduction of pesticide use, are of crucial importance for the preservation of natural resources and the long-term stability of rural communities (Pretty, 2008; Smith et

al., 2019). In this sense, measuring the sustainability of agriculture through a set of indicators becomes necessary in order to systematically identify positive and negative trends.

Monitoring the integration of environmental problems of agriculture in the European Union is based on the system of agri-environmental indicators (AEI), developed by Eurostat and the European Environment Agency (European Environment Agency, 2023; Eurostat, 2023). These indicators include various aspects of agricultural practice - from greenhouse gas emissions and energy consumption, through the use of pesticides and environmental risks, to the spread of organic production (Dimitrijević, 2025). Their comparability and standardization make them a suitable tool for evaluating and shaping agricultural policies at the EU level. However, a large number of indicators and their mutual dependence make interpretation difficult, so multivariate dimensionality reduction methods, such as principal component analysis (PCA), are increasingly used in the analysis.

Due to the large number of indicators and their interdependence, researchers often use multivariate statistical methods such as principal component analysis (PCA) and factor analysis. Dabkiene et al., (2021) developed the concept of “agri-environmental footprint” using PCA and multi-criteria analysis to reduce complexity and build a unique index. A similar methodological approach was proposed by Gómez-Limón et al., (2020), who point out that PCA can be used not only for dimensionality reduction, but also for the objective determination of weights when constructing composite indicators.

The literature review also indicates the growing use of composite indicators in the agricultural sector. Magrini & Giambona, (2022) provide a systematic review of methodologies, highlighting the advantages and limitations of different approaches, including PCA-weights, equal weighted indices and expertly determined weights. Their findings suggest that the use of PCA is particularly useful in situations where there are a large number of highly correlated indicators, as is the case with AEI.

Empirical research conducted at the level of the European Union additionally confirms the importance of the application of multicriteria and multivariate methods in the analysis of agricultural sustainability. Belinska, et al., (2020) analyzed regional differences within the EU using a set of indicators that reflect the ecological context of development, pointing to pronounced geographical and structural disparities between the countries of Central, Western and Southern Europe. Their findings confirm that variations in sustainability performance are closely related to economic development, agricultural structure, and environmental policies. In a more recent work, Marković et al., (2024) the authors conducted an analysis of the performance of agri-ecological sustainability in EU countries using the multi-criteria method and principal component analysis (PCA). The results of their study indicated the existence of significant differences between member states, with Western and Northern European countries achieving better results thanks to a higher share of organic production, more efficient use of energy and less use of pesticides. The authors point out that combining AEI indicators and PCA enables a more comprehensive insight into real differences in sustainability and contributes to the development of more precise instruments for creating agricultural policies.

## Materials and methods

### Dataset Description

The dataset uses Eurostat data on Agri-environmental Indicators (AEIs) for 2017 and 2023 to assess the relationship between agriculture and the environment and the integration of environmental goals into the EU's Common Agricultural Policy (CAP). It originally included 28 indicators grouped into six themes: (1) Agricultural Land Use, (2) Input Use, (3) Emissions and Climate Change, (4) Biodiversity, (5) Soil and Water, and (6) Socio-economic Factors. Due to missing data, Luxembourg and Malta were excluded, resulting in a final dataset of 25 EU countries and 9 selected indicators. Only indicators with complete data for both years and countries were used in the analysis. The data set is shown in Table 1.

**Table 1.** List of used indicators

Agri-environmental indicator	Sub indicator	Unit of measure:	Code
Climate	Greenhouse gas emissions from agriculture (Greenhouse gases (CO <sub>2</sub> , N <sub>2</sub> O in CO <sub>2</sub> equivalent, CH <sub>4</sub> in CO <sub>2</sub> equivalent, HFC in CO <sub>2</sub> equivalent, PFC in CO <sub>2</sub> equivalent, SF <sub>6</sub> in CO <sub>2</sub> equivalent, NF <sub>3</sub> in CO <sub>2</sub> equivalent)Percentage	percentage	GHG
Environment: Energy	Energy use: Gross available energy	Thousand tonnes of oil equivalent	EUGAE
	Production of renewable energy - Complete energy balances: Primary production		REPP
	Production of renewable energy - Complete energy balances: Recovered and recycled products		RERRP
Societal demand on food and health	Area under organic farming	Percentage of total utilised agricultural area	OF
	Pesticide sales: Fungicides and bactericides	kilogram	PSFB
	Pesticide sales:Herbicides, haulm destructors and moss killers		PSHDMK
	Pesticide sales:Insecticides and acaricides		PSIA
	Pesticide risk: Harmonised risk indicator 1 for pesticides by categorisation of active substances	Index, 2011-2013 average =100	PSI

Source: Authors' calculations based on Eurostat data.

## Statistical Tools and Techniques

For the purposes of this research, the Principal Component Analysis (PCA) method will be used, which is one of the most commonly applied multivariate techniques for data dimensionality reduction. PCA enables the identification of latent structures in a data set by correcting the intercorrelations between variables and reducing a large number of initial indicators to a smaller number of components that retain most of the variance. In this way, factors are obtained that are orthogonal to each other and that facilitate further interpretation and interpretation of the underlying patterns in the data. As part of the preliminary adequacy check, the Kaiser-Meyer-Olkin (KMO) test and Bartlett's test of sphericity will be used to determine whether the data meet the conditions for applying PCA. Based on the obtained PCA results, the main factors that explain the largest part of the variance will be extracted and will be used in further analysis.

The generalized forms of the estimated principal components in the linear combination of the indicators can be expressed as follows, after Manly's (1994) suggestion:

$$Z_1 = a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n$$

$$Z_2 = a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n$$

$$Z_s = a_{s1}x_1 + a_{s2}x_2 + \dots + a_{sn}x_n$$

Where,

The number of retrieved extracted components is represented by the variables  $z_1$ ,  $z_2$  and  $z_s$ ; the factor loadings linked to the  $x_{ij}$  indicators on a specific main component are denoted by  $a_{ij}$ ; the value of the indicator for the specific case or sample is denoted by  $x$ . The total number of indicators used to create a specific composite index is denoted by  $n$ .

## Results

In this research, principal component analysis (PCA) was conducted to reduce the dimensionality of the data and extract the main factors. After checking the level of adequacy of application using the KMO method and Bartlett's test, PCA was applied to the standardized values of the variables (Linting et al., 2007). The number of factors was determined based on the Kaiser criterion (eigenvalue > 1) and scree diagram, and then rotation was performed for a clearer interpretation of the obtained factor structure.

**Table 2.** KMO and Bartlett's Test

Year		2017	2023
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.528	0.544
Bartlett's Test of Sphericity	Approx. Chi-Square	271.943	224.980
	df	45	36
	Sig.	0.000	0.000

*Source:* Authors' calculations

When checking the adequacy of the data for factor analysis, the Kaiser-Meyer-Olkin (KMO) index and Bartlett’s test of sphericity were calculated (Table 2). The obtained value of the KMO test is 0.528/0.544, which according to Kaiser (1974) and Hair et al. (2019) is in the “weak but acceptable” category. Thus, although the value of the KMO index is not high, it exceeds the minimum threshold of 0.50, which means that factor analysis can be conducted, but the results should be interpreted with some caution (Field, 2013; Hutcheson & Sofroniou, 1999). Bartlett’s test of sphericity ( $\chi^2 = 271.943/224.980$ ;  $df = 45/36$ ;  $p < 0.001$ ) shows that there are enough significant correlations between the variables, which further confirms the justification of applying factor analysis.

The analysis of descriptive indicators for EU countries in the period 2017 vs. 2023 (Table 3.) indicates two parallel trends. On the one hand, there is a reduction in greenhouse gas emissions, a significant increase in the production and availability of energy from renewable sources, which confirms progress in the direction of climate and energy sustainability. On the other hand, there is a strong increase in the use of pesticides and chemical agents, while the growth of organic agriculture is relatively slow, which indicates the continued dependence of agriculture on intensive inputs and challenges in the transition to more sustainable practices.

**Table 3.** Descriptive Statistics results

Indicator	N (2017, 2023)	Minimum (2017)	Minimum (2023)	Maximum (2017)	Maximum (2023)	Mean (2017)	Mean (2023)	Std. Deviation (2017)	Std. Deviation (2023)
PSI	25	5.30	24.00	33.10	96.00	11.9760	47.0400	6.72175	21.76097
GHG	25	2826.81	6.00	324280.63	36.20	61085.5048	13.7400	81275.54001	7.00643
EUGAE	25	144.70	2844.68	131768.04	257206.48	25627.2179	53295.7108	33428.24452	67873.28629
REPP	25	0.00	268.37	484.85	122122.79	66.0990	22111.7928	136.06476	28308.49975
RERRP	25	1.66	0.00	23.37	664.31	8.9264	64.8714	5.80481	145.85369
OF	25	117032.00	2.95	37982029.00	23.37	6255205.4000	11.5968	10713497.93412	6.05267
PSFB	25	138932.00	117659.00	30252649.00	26115431.00	4769842.3200	4620759.6400	7123997.73356	7851533.25904
PSHDMK	25	24998.00	119470.00	14548167.00	29905629.00	1539690.5600	4344480.1200	3106822.17974	6656276.77906
PSIA	25	41.00	4880.00	163.00	15948944.00	93.2000	1759429.8800	25.99840	3749854.19886

Source: Authors’ calculations

When we talk about the indicators individually, the PSI (pesticide risk indicator) recorded an increase in the average value from 11.98 (2017) to 47.04 (2023), with increased variability (Std. dev. 6.72 → 21.76), which indicates the growth of risks associated with the use of pesticides in agriculture. GHG emissions from agriculture decreased on average (from 61,085.5 to 13,740), which suggests progress in reducing emissions, although in 2017 there were extremely high values in certain countries (maximum over 324,000), while in 2023 the distribution was more uniform (Std. dev. significantly lower). EUGAE (gross available energy) shows a significant growth of the average (from 25,627 to 53,296), which indicates increased available energy in the

EU. REPP (primary renewable energy production) also recorded significant growth (from 66.9 to 22,111), which confirms the trend of strengthening renewable energy sources. RERRP (recovered and recycled products) increased on average (from 5.9 to 64.9), which indicates progress in the circular economy and better utilization of waste. Indicator OF (organic farming) recorded stagnation and a slight increase in the average value (from 10,734 to 11,968), which indicates that the share of areas under organic production is growing slowly compared to energy indicators. PSFB, PSHDMK and PSIA recording very high average values in 2023 compared to 2017 (e.g. fungicides and bactericides from 1,074,387 to 11,596,800; herbicides from 310,682 to 6,652,676; insecticides from 25.99 to 3,749,284), indicating strong growth in pesticide use and chemical agents in EU agriculture.

Table 4 shows the results of the principal component analysis (PCA) for 2017 and 2023, where two components are separated that group the indicators depending on their connection.

**Table 4.** Summary statistics of the principal component analysis.

Year	2017		2023	
	Component		Component	
	1	2	1	2
GHG	-.188	-.622	-.196	-.044
EUGAE	.981	.065	.987	.037
REPP	.940	-.007	.933	.057
RERRP	.672	.095	.661	-.124
OF	-.199	.747	-.080	.889
PSFB	.729	-.006	.805	.120
PSHDMK	.905	-.125	.894	-.017
PSIA	.872	.097	.867	.112
PSI	-.078	.709	-.153	.809
Extraction Method: Principal Component Analysis.				
a. 2 components extracted.				

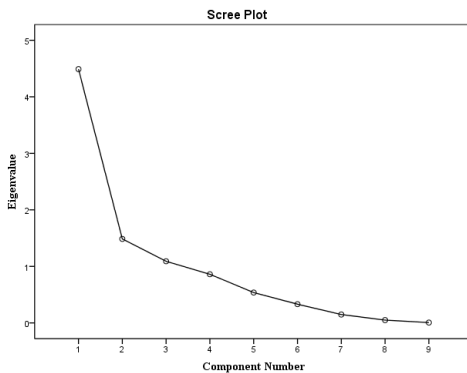
*Source:* Authors' calculations

The PCA results show that in both observed years the indicators are distributed in two clear clusters. In 2017, the first component is heavily loaded with indicators related to energy efficiency and renewable sources (EUGAE, REPP, RERRP), as well as organic agriculture (OF) and pesticide consumption (PSFB, PSHDMK, PSIA), while the second component mostly includes indicators of pesticide risk (PSI) and GHG emissions. In 2023, the structure partially changes - the first component still gathers energy indicators and organic agriculture, but the pesticide risk (PSI) is still clearly distinguished as a dominant indicator of the second component, which indicates its special role in the differentiation of countries. This suggests that over time EU policies have contributed

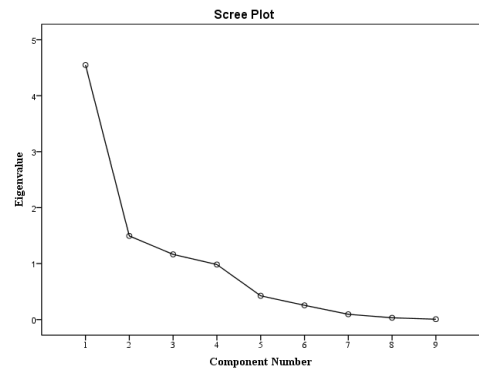
to the homogenization of countries in terms of energy and agricultural indicators, while pesticides continue to be a key factor in differences between countries.

Based on the scree plot diagram, a clear “break” point can be seen after the second component, which confirms that it is justified to keep exactly two factors. This result is also consistent with Kaiser’s criterion (value of latent roots above 1), which further justifies the extraction of a two-component structure. The first component explains most of the variance and is related to energy and agricultural indicators, while the second component includes primarily risks associated with pesticides and greenhouse gas emissions. Such a structure indicates that the EU countries in the analyzed period are differentiated on the basis of two basic dimensional directions - sustainability in energy and agriculture, on the one hand, and environmental risks from pesticides, on the other.

**Figure 1.** Scree plot of the principal component analysis, 2017



**Figure 2.** Scree plot of the principal component analysis, 2023



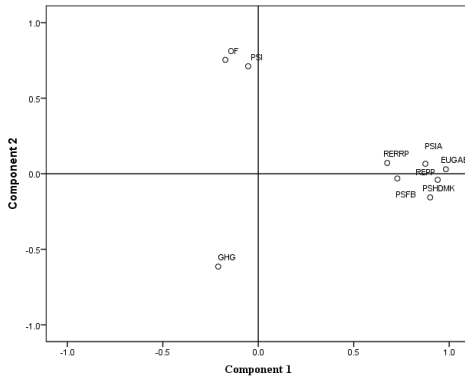
*Source:* Authors’ calculations

Further, the Figures 1 and Figures 2 shows Scree plot diagrams for 2017 and 2023, which show the distribution of characteristic values (eigenvalues) by components. In both cases, a sharp drop in value is noticeable after the second component, which indicates the so-called “elbow point” after which the contribution of each subsequent component significantly decreases. Based on Kaiser’s criterion (eigenvalue > 1) and visual assessment of the plot, two principal components were retained that together explain the largest part of the total variance of the data.

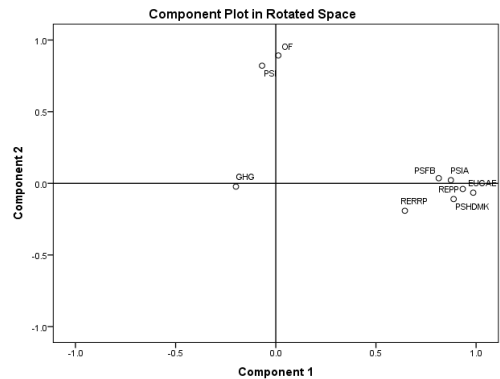
This result confirms that the structure of agri-environmental indicators in both observed years can be reduced to two dominant dimensions. The first component includes indicators related to energy efficiency and renewable energy sources, while the second component reflects the dimension of the pressure of agriculture on the environment through gas emissions and the use of pesticides. By comparing 2017 and 2023, it can be concluded that the stability of the indicator structure is high, which indicates the persistence of the basic patterns of sustainability within European agriculture.

In order to determine the position of the observed variables, a rotated component diagram was arranged (Figures 3 and 4). Based on the rotated component diagrams for 2017 and 2023, a relatively similar structure of the factor distribution of variables can be observed, with certain differences in the intensity of connection between individual indicators.

**Figure 3.** Component plot in Rotated Space, 2017



**Figure 4.** Component plot in Rotated Space, 2023



*Source:* Authors' calculations

Based on the rotated component diagrams for 2017 and 2023, a relatively similar structure of the factor distribution of variables can be observed, with certain differences in the intensity of connection between individual indicators.

In 2017, the variables related to the use of energy and pesticides (EUGAE, REPP, RERRP, PSFB, PSHDMK, PSIA) were grouped with the first component, indicating that it dominantly reflects the energy-agricultural factor related to the intensity of production. In contrast, the variables OF (organ farming) and PSI (pesticide risk indicator) are positioned next to the second component, which indicates a separate dimension related to sustainability and ecological practices in agriculture. The variable GHG (greenhouse gases) is in the opposite quadrant, suggesting a negative association with sustainability factors.

In 2023, the structure is similar, but the components are more compact and stable. Variables related to pesticides and energy use (PSFB, PSHDMK, PSIA, REPP, RERRP, EUGAE) are again grouped with the first component, confirming the existence of the same latent factor that describes the intensity of production activities. The variables OF and PSI still form a separate set connected to the second component, which still represents an ecologically sustainable approach. Changes in the distribution of variables between the two years indicate a slight strengthening of the links within the first component, which may suggest increased homogeneity of indicators related to agricultural and energy activities.

By calculating the composite index of agri-environmental performance, the comparison of EU countries and their ranking in 2017 and 2023 is enabled (Table 5). The obtained results indicate changes in the positioning of individual countries - while some have made progress through reducing greenhouse gas emissions, increasing the share of renewable energy and expanding areas under organic agriculture, other countries still record a high level of dependence on pesticides and intensive use of chemical agents.

In this analysis, the index is constructed so that more negative values (e.g. -0.62 for Cyprus, -0.54 for Croatia) indicate lower emissions, more efficient energy use and a higher share of sustainable practices — hence better agri-environmental performance. Conversely, more positive values (e.g. +1.63 for Germany or +1.59 for France) indicate higher environmental burdens, which means poorer sustainability performance. As can be seen, since negative values of the composite index indicate better agri-environmental performance, countries with the lowest indices (e.g. Cyprus, Croatia, Greece) occupy the top positions in the ranking, while more positive values (e.g. Germany and France) reflect poorer performance and are positioned at the bottom of the list. Thus, the results show that Cyprus, Croatia and Greece maintain the most favourable agri-environmental performance in both 2017 and 2023, indicating a relatively balanced relationship between agricultural activities and environmental protection. In contrast, Germany and France consistently record the highest (positive) index values, reflecting a lower level of sustainability due to intensive agricultural production and increased greenhouse gas emissions.

Comparing the two periods, a relative stability in the ranking of countries is observed, with a slight improvement in the case of Slovenia and Hungary, which record progress in the implementation of sustainable agricultural practices and energy efficiency. The reduction in differences between middle-ranking countries indicates a gradual convergence of agri-environmental performance within the European Union. These results are consistent with the findings of the PCA analysis, where the same countries showed the highest values of the first component associated with efficient resource management, renewable energy and reduced gas emissions. At the same time, countries with a higher index (such as Germany and France) have a higher load in the second component reflecting intensive production and higher energy impact.

**Table 5.** Composite index of agri-environmental of EU countries 2017 vs.2023

Country	Composite index 2017	Rank 2017	Country	Composite index 2023	Rank 2023
Cyprus	-0.62	1	Cyprus	-0.61	1
Croatia	-0.54	2	Croatia	-0.59	2
Greece	-0.51	3	Slovenia	-0.49	3
Bulgaria	-0.42	4	Greece	-0.49	4
Slovakia	-0.42	5	Slovakia	-0.44	5
Portugal	-0.4	6	Bulgaria	-0.41	6
Slovenia	-0.37	7	Hungary	-0.41	7

Country	Composite index 2017	Rank 2017	Country	Composite index 2023	Rank 2023
Denmark	-0.3	8	Belgium	-0.4	8
Belgium	-0.3	9	Romania	-0.3	9
Romania	-0.28	10	Czechia	-0.23	10
Hungary	-0.26	11	Ireland	-0.18	11
Czechia	-0.18	12	Lithuania	-0.11	12
Ireland	-0.15	13	Netherlands	-0.11	13
Sweden	-0.09	14	Denmark	-0.1	14
Lithuania	-0.07	15	Portugal	-0.1	15
Finland	-0.06	16	Sweden	0	16
Latvia	-0.04	17	Finland	0.04	17
Estonia	0.05	18	Latvia	0.05	18
Austria	0.1	19	Estonia	0.08	19
Netherlands	0.25	20	Austria	0.16	20
Poland	0.44	21	Poland	0.17	21
Italy	0.53	22	Italy	0.51	22
Spain	0.64	23	Spain	0.73	23
France	1.37	24	Germany	1.59	24
Germany	1.63	25	France	1.61	25

*Source:* Authors' calculations

The results obtained are in line with previous research (e.g. Eurostat, 2023; OECD, 2022; Gómez-Limón & Sanchez-Fernandez, 2010), which indicate the existence of a clear difference between Mediterranean countries that tend more towards sustainable production systems and Western European countries where a high degree of agricultural industrialization dominates. Overall, the analysis confirms that, despite moderate improvements, structural differences in agri-environmental performance among EU Member States remain present.

## Conclusion

The analysis of agri-environmental indicators provides a comprehensive insight into the state and dynamics of the sustainability of agriculture in the countries of the European Union. By comparing the data for 2017 and 2023, progress can be seen in certain dimensions, especially with regard to the increase in the share of organic production and the growth of energy production from renewable sources, while greenhouse gas emissions and the use of pesticides are still a significant challenge. These results confirm that the transition towards sustainable production models is progressing, but unevenly among member states.

The application of principal component analysis (PCA) proved to be a useful method for identifying the basic dimensions of sustainability and reducing a complex set of

indicators to a smaller number of representative factors. The overall findings show two contrasting trends in EU agriculture: Positive developments have been achieved in reducing GHG emissions and increasing production and availability of energy from renewable sources, with growth in recycling. Negative trends are observed through the increase in the risk and scope of pesticide use, while the participation of organic agriculture is increasing very slowly. These results suggest that the EU is simultaneously making progress in the energy and climate sectors, but still has challenges in the area of chemical dependency of agriculture and the transition to more sustainable practices.

Also, the results indicate that future EU policies should be aimed at reducing sustainability differences among member states through targeted incentives and knowledge sharing. The Common Agricultural Policy (CAP) should strengthen support for organic production, energy efficiency and reduction of pesticide use. The inclusion of composite agri-environmental indices in the CAP monitoring system can contribute to a more precise measurement of progress and more efficient implementation of the goals of the European Green Deal.

This research faces several limitations. First, the availability and consistency of data varies between countries and years, which may affect the precision of the estimate. Second, the choice of indicators was conditioned by the availability of data at the Eurostat level, so some important aspects of sustainability could not be included. Third, the methodological framework based on PCA analysis depends on correlations among indicators and does not take into account causal relationships. In this regard, future research can be conducted using more advanced methods of multi-criteria analysis (eg DEA, TOPSIS or fuzzy-MCDM) and combining quantitative and qualitative approaches.

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### **Conflict of interests**

The authors declare no conflict of interest.

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