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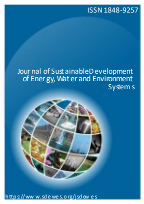

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Original Research Article

The Water, Energy, Food, and Ecosystems Nexus through Sustainable Development Goal Interactions: A Temporal Dynamics Approach

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ABSTRACT

The Water, Energy, Food, and Ecosystem nexus highlights the interconnections between water, energy, agriculture, and ecosystems, emphasising cross-sectoral coordination for sustainable development. This study examines the nexus across the twenty-seven European Union member states through the lens of Sustainable Development Goals 2, 6, 7, and 15, using time series data from 2001 to 2023. Countries are first clustered based on Sustainable Development Goal trends using Euclidean distance and Dynamic Time Warping, followed by a comparison of results with an existing classification. Subsequently, a Vector Autoregressive model is applied to analyse interactions among the goals and identify key drivers within the Water, Energy, Food, and Ecosystem nexus. Results show consistent dependencies among the Sustainable Development Goals at both the European Union and country levels, with some country-specific variations aligning with cluster affiliations. These findings enhance the understanding of goal interdependencies and inform policy actions to strengthen underdeveloped linkages, supporting the effective implementation of the Water, Energy, Food, and Ecosystem nexus in the European Union.

KEYWORDS

Water-Energy-Food-Ecosystem nexus, Sustainable development goals, European Union, Clustering, Vector autoregressive model, Artificial intelligence.

INTRODUCTION

The Water-Energy-Food-Ecosystem Nexus (WEFE Nexus) highlights the interdependence among water, energy, and food security, as well as the critical role of ecosystems in the sustainability of these resources. This approach has gained importance in the context of climate change and the increasing pressure on natural resources, driving the need for integrated models to analyse and manage them.

The concept of the Water-Energy Nexus emerged in the early 2000s, emphasising the interdependence between water and energy. It was recognised that energy production requires water (for example, cooling in thermal plants or hydropower generation) and that water supply

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demands energy (for pumping, treatment, and distribution). Studies [1] and [2] address the Water-Energy nexus from a methodological perspective, analysing interactions between the two resources and proposing optimisation models to improve efficiency.

Later, the Water-Energy-Food Nexus (WEF Nexus) expanded its analysis to include the food sector, recognising that food production also depends on water and energy. This approach gained momentum after the UN Rio+20 conference (2012) and was promoted by organisations such as the United Nations Environment Programme (UNEP) and the World Economic Forum, which highlighted the importance of integrated resource governance. In this context, various studies have explored the relationships between the WEF Nexus and the Sustainable Development Goals (SDGs). For example, the study in [3] examines the challenges of the WEF nexus in South Asia, where cereal production subsidies have increased water and energy demand, resulting in environmental degradation and health issues. The lack of coordination between sectors has led to unsustainable resource use, hindering the achievement of SDGs 2 (Zero Hunger), 6 (Clean Water and Sanitation), and 7 (Affordable and Clean Energy). More recently, the nexus framework has evolved into the Water-Energy-Food-Ecosystem (WEFE) nexus, which explicitly incorporates ecosystems to capture broader environmental feedbacks affecting resource sustainability. Ecosystems play a key role in regulating water availability, maintaining soil productivity, and supporting biodiversity, which in turn sustain food and energy systems. Consequently, integrating ecosystems into nexus analyses allows for a more comprehensive understanding of sustainability challenges and policy trade-offs. This broader perspective has been increasingly promoted by institutions such as the Food and Agriculture Organisation (FAO) and the European Union, which advocate holistic resource governance strategies.

In parallel with the development of nexus approaches, the Sustainable Development Goals (SDGs) have emerged as a global framework for guiding sustainability policies. Several studies have highlighted the strong conceptual links between nexus components and specific SDGs. In particular, frequently identified core goals within the WEFE nexus framework are: SDG 2 – food security, SDG 6 – water management, SDG 7 – energy access, and SDG 15 – life on land. For example, [4] shows that the food–energy–water nexus is closely connected with SDGs 2, 6, and 7, while [5] identifies these goals as central to the analysis of sustainable targets within WEFE nexus initiatives in the Mediterranean region. Similarly, [6] emphasises that nexus approaches are explicitly recognised within several SDGs, particularly SDGs 2, 6, 7, 13, and 15. In the same line, [7] investigates the interactions within the Food-Energy-Water (FEW) nexus by analysing the relationships among six SDGs, with particular emphasis on SDGs 2, 6, 7, and 15, across different regions of China, employing a panel vector autoregression (PVAR) model to quantify the interdependencies among these goals.

From a policy perspective, [8] demonstrates that implementing the WEFE nexus can support the simultaneous achievement of multiple SDGs, especially those related to access to land, food, water, and energy. Other studies have extended this perspective to broader nexus frameworks. For example, [9] proposes the Water-Energy-Land-Food-Climate nexus and shows that SDGs 2, 6, 7, and 15 play a key role in achieving integrated sustainability policies. In addition, [10] develops a Water-Energy-Food Nexus Index based on indicators closely aligned with SDGs 2, 6, and 7 and applies clustering techniques to classify countries by nexus performance.

Other studies also examine the integration of the WEFE nexus within the SDG framework. For instance, [11] proposes a governance-oriented approach to the WEFE nexus to support the design of coherent and integrated public policies, highlighting its potential implications for the effective implementation of multiple SDGs. Additionally, [12] conducts a PRISMA-based systematic review of 183 publications, most of which explicitly address the SDGs within the WEF nexus. Although the review primarily focuses on WEF interactions, many of the analysed studies incorporate ecosystem-related dimensions that are closely aligned with the WEFE framework. Finally, [13] presents a systems modelling study that explores the complex interdependencies of the WEFE nexus in a real-world setting in Spain, providing insights into sustainable resource management and illustrating how integrated nexus approaches can advance SDGs related to water, energy, food security, and ecosystem preservation.

Empirical studies have also explored interactions between nexus components using different methodological approaches. The study in [14] examines the relationship between the WEF nexus and the 17 SDGs through fuzzy cognitive maps, providing policymakers with a tool to prioritise investments, and identifying SDGs 2, 6, and 7 as the most strongly influenced by nexus dynamics. Similarly, [15] analyses the internal mechanisms of the water–energy–food nexus in China using a Structural Vector Autoregression (SVAR) model, highlighting dynamic interactions and time-lag effects between these sectors. Other works have examined nexus–SDG relationships in different regions. For example, [16] analyses the Water-Energy-Food nexus in the Horn of Africa and emphasises the challenges these countries face in achieving SDGs 2, 6, and 7.

Beyond these approaches, several studies have examined broader interactions among SDGs from a systemic perspective. For instance, [17] proposes a cross-impact matrix methodology to analyse how progress in one SDG influences others. Their framework introduces a seven-point typology of interactions ranging from negative trade-offs to positive synergies and highlights strong relationships between SDG 6 (water) and SDG 7 (energy). Such systemic analyses illustrate the complexity of interactions within the SDG framework and underline the importance of quantitative tools capable of capturing these dynamic relationships.

Despite the growing literature on nexus approaches and interactions with the SDGs, several research gaps remain. First, many studies focus on conceptual frameworks or qualitative analyses of nexus relationships, while relatively few provide quantitative assessments of the dynamic interactions between SDGs over time. Second, empirical analyses are often conducted at the country or specific case-study level, and there is still limited evidence regarding the dynamic functioning of the WEFE nexus within the European Union. Third, although clustering techniques have been applied to nexus indicators in previous studies, these analyses typically rely on static indicator values rather than the temporal evolution of SDG indicators.

This study aims to address these gaps by analysing the WEFE nexus through the lens of the SDGs using time-series data for the European Union and its 27 member states during the period 2001–2023. The analysis focuses on SDG 2 (Zero Hunger), SDG 6 (Clean Water and Sanitation), SDG 7 (Affordable and Clean Energy), and SDG 15 (Life on Land), which correspond to the food, water, energy, and ecosystem dimensions of the WEFE nexus. Within the WEFE nexus framework, SDGs 2, 6, 7, and 15 correspond to the food, water, energy, and ecosystem dimensions, respectively. Food production (SDG 2) relies heavily on water and energy resources and may exert pressure on ecosystems. Water management (SDG 6) is essential for both agricultural and energy systems, while energy production (SDG 7) often depends on water resources and ecosystem services. Finally, terrestrial ecosystems (SDG 15) provide essential services such as soil fertility, biodiversity, and water regulation that sustain food and energy systems. Considering these interdependencies, these four SDGs provide an appropriate empirical representation of the WEFE nexus.

Although the literature shows that other SDGs are also related to the nexus, such as SDG 1 (poverty reduction) or SDG 13 (climate action), SDGs 2, 6, 7, and 15 are consistently identified as the most directly connected to the core components of the WEFE framework [16], [17]. The selection of these four goals is therefore conceptually justified by the existing literature and also motivated by methodological considerations. Vector Autoregressive models require a sufficient number of observations relative to the number of variables included in the system. Since the available SDG time series cover the period 2001–2023 and provide only twenty-four observations, limiting the number of variables helps ensure the stability and reliability of the estimated VAR(p) models.

The empirical analysis relies on the SDG indicator database compiled in the European Sustainable Development Report 2023/24 [18], which provides annual scores measuring countries' performance across the SDGs. The report includes the SDG Index and Dashboards. The SDG Index is a score based on indicators that ranks countries according to their overall performance across the 17 SDGs. The Dashboards are visual charts that provide a detailed view of each country's performance on each goal. They use a traffic light-style colour system:

- Green: Indicates that the country is close to achieving or has already achieved the goal.
- Yellow or orange: Shows partial progress, but with remaining challenges.
- Red: Highlights areas that require urgent attention and where progress is slower.

Approximately 70% of the indicators come from official statistics (mainly from European Commission services), while 30% are sourced from non-official data (NGOs, academia). Using this dataset, the study considers time series for the four selected SDGs for each of the 27 EU member states, as well as aggregated series for the European Union as a whole. The methodology section will detail the indicators and the analysis used to calculate the indices for each SDG.

The analysis is structured in two stages. First, a time-series clustering analysis is applied to the SDG trajectories of EU countries to identify patterns in their evolution. The clustering is performed using the k-means algorithm [19] with two alternative distance measures: Euclidean distance and Dynamic Time Warping (DTW) [20]. While Euclidean distance compares the absolute levels of indicators, DTW measures similarity between time series by allowing temporal misalignments, making it suitable for identifying similar development trajectories occurring at different times.

Second, the dynamic interactions between the four SDGs are analysed using a Vector Autoregressive VAR(p) model [21]. This model explains the evolution of each variable as a function of its own past values and those of the other variables in the system, allowing the identification of dynamic interdependencies between SDGs.

The contributions of this paper can be summarised as follows:

1. Integration of WEFE nexus and SDG indicators, providing an empirical framework linking SDGs 2, 6, 7, and 15 with the WEFE nexus in the European context.
2. Time-series clustering of SDG trajectories, analysing similarities in the temporal evolution of SDG indicators across EU countries.
3. Dynamic modelling of SDG interactions, using VAR(p) models to investigate the interdependencies between SDGs and identify potential nexus relationships.
4. EU-wide and country-level analysis, comparing the interactions observed at the EU level with those found for individual member states.

By combining time-series clustering methods with VAR modelling, this research provides new empirical evidence on both the structural similarities between EU countries and the dynamic interactions between SDGs, contributing to a better understanding of how the WEFE nexus operates within the European sustainability framework.

METHODS

In this section, the indicators used to generate the time series for SDGs 2, 6, 7, and 15 are explained, as well as the methodology applied for clustering countries and implementing the Vector Autoregressive model based on these time series. The analysis focuses on SDGs 2, 6, 7, and 15, which represent the food, water, energy, and ecosystem dimensions of the Water–Energy–Food–Ecosystem (WEFE) nexus. As discussed in the introduction, these goals are widely identified in the literature as the SDGs most directly linked to the core components of the WEFE framework [16], [17]. Although other SDGs are also related to nexus interactions, limiting the analysis to these four goals is both conceptually justified and methodologically appropriate, since the available time series (2001–2023) provide a limited number of observations and the Vector Autoregressive VAR(p) model requires a balanced relationship between the number of variables and observations to ensure stable estimation.

The indicators used in this study correspond to the SDG scores reported in the European Sustainable Development Report 2023/24 [18], which provides standardised measures of countries' performance across each goal. The indicator framework used in [18] is similar to that of [22]; however, [22] takes a more global and comparative approach, while [18] adapts the indicators to the European context and links them to EU policymaking.

Indicators

The selection of indicators in this study follows the conceptual structure of the Water–Energy–Food–Ecosystem (WEFE) nexus, linking SDG 6 to water resources, SDG 7 to energy systems, SDG 2 to food systems, and SDG 15 to ecosystems.

When comparing the selected indicators with those used in [10] to analyse the Water-Energy-Food (WEF) nexus, many indicators employed in this study capture similar dimensions of resource use and sustainability. For example, in the water dimension, indicators related to access to water and sanitation services, freshwater withdrawals, and wastewater treatment correspond conceptually to commonly used WEF indicators such as access to drinking water, sanitation services, and freshwater withdrawals. In the energy dimension, indicators such as the share of renewable energy and CO_2 emissions from electricity generation capture key aspects of energy sustainability, as reflected in WEF studies through variables such as renewable energy consumption, electricity access, and CO_2 emissions. In the food dimension, indicators related to agricultural productivity, dietary patterns, and environmental impacts of agriculture (e.g., ammonia emissions) reflect core elements of food system performance similar to those measured in previous WEF studies through variables such as cereal yields, food production value, and nutritional indicators.

A key difference from earlier WEF analyses is that the present study explicitly incorporates an ecosystem dimension, consistent with the WEFE nexus framework. Accordingly, additional indicators related to biodiversity conservation, water quality, and ecosystem pressures are included to capture the environmental feedback between natural ecosystems and resource systems. Overall, the selected indicators provide a comprehensive representation of the four core components of the WEFE nexus while maintaining conceptual consistency with the indicators used in previous WEF nexus studies.

The following paragraphs describe the indicators used to compute the indices for SDGs 2, 6, 7, and 15. For SDG 2, the selected indicators include obesity prevalence (BMI ≥ 30, % of the adult population), yield gap closure [%], which measures the necessary increase in agricultural productivity to reach optimal levels, the Human Trophic Level (best 2, 3 worst), assessing the ecological sustainability of human diets [23], agricultural ammonia emissions [kg/ha], quantifying ammonia released into the environment from agricultural activities, and exports of pesticides banned in the EU [kg per 1,000 inhabitants], indicating the amount of EU-prohibited pesticides exported to other countries.

For SDG 6, the indicators considered are the percentage of the population without access to a toilet, shower, or flushing system at home, water consumption embedded in imports [m^3/person], freshwater withdrawal as a percentage of the long-term available water average, the percentage of the population connected to at least secondary wastewater treatment, the percentage using safely managed drinking water services, and the percentage using safely managed sanitation services.

Regarding SDG 7, the indicators include the percentage of the population unable to keep their home adequately warm, the share of renewable energy in gross final energy consumption, and CO_2 emissions from fuel combustion per unit of electricity generated [$MtCO_2$/TWh].

For SDG 15, the selected indicators are the Red List Index for species survival (worst 0, 1 best), the average proportion of protected areas in key terrestrial biodiversity sites, biochemical oxygen demand in rivers [mg O_2/L], threats to terrestrial and freshwater biodiversity embedded in imports (per million inhabitants), the average proportion of protected areas in key freshwater biodiversity sites, and nitrate concentration in groundwater [mg NO_3/L].

The selected indicators provide data for computing SDG indices from 2000 to 2023. To ensure comparability, all indicators were normalised on a scale from 0 to 100, where 0 represents the worst performance and 100 the best. This was achieved by defining upper and lower limits for each indicator and applying a linear transformation. To compute the SDG Index, scores for each goal were calculated as the arithmetic mean of the corresponding indicators, all scaled to 0–100. Equal weights were assigned to aggregate indicator scores into SDG scores.

Clustering

In this section, we describe the methodology used to perform a clustering analysis of European Union (EU) countries based on two time-series distance measures. For the sake of simplicity and consistency throughout the analysis, each country is assigned a numerical identifier as follows: 1. Austria, 2. Belgium, 3. Bulgaria, 4. Cyprus, 5. Czechia, 6. Germany, 7. Denmark, 8. Spain, 9. Estonia, 10. Finland, 11. France, 12. Greece, 13. Croatia, 14. Hungary, 15. Ireland, 16. Italy, 17. Lithuania, 18. Luxembourg, 19. Latvia, 20. Malta, 21. The Netherlands, 22. Poland, 23. Portugal, 24. Romania, 25. Slovakia, 26. Slovenia, and 27. Sweden.

Clustering process using the euclidean distance between time series. The objective is to group the 27 EU countries into clusters for each SDG (2, 6, 7, and 15) based on the similarity of their time series from 2000 to 2023. This approach helps identify common patterns in their evolution over time and allows for a comparison between the resulting clusters and the colour-based grouping mentioned earlier.

Each EU country has a time series of 24 values (corresponding to the years 2000 to 2023) for each SDG. These time series can be represented as vectors in the Euclidean space R^{24}, where each vector component corresponds to the SDG index for a given year.

Euclidean distance in R^{24} is a similarity measure used to compare time series. For two countries with SDG indices $x = (x_1, \dots, x_{24})$ and $y = (y_1, \dots, y_{24})$, the Euclidean distance is defined as:

$$d(x,y) = \sum_{i=1}^{24} (x_i - y_i)^2 \tag{1}$$

where x_i and y_i are the SDG index values of the two countries for year *i*; a smaller distance indicates greater similarity between the time series.

Clustering is an unsupervised classification method, and the process involves the following steps:

1. Distance calculation: Construct a distance matrix for the 27 time series using the Euclidean distance formula. Since the Euclidean distance is symmetric ($d(x,y) = d(y,x)$), the resulting matrix will have dimensions 27×27.
2. Application of the *k*-means clustering algorithm: This algorithm partitions the data into k clusters by minimising the sum of distances within each cluster.
3. Assigning countries to clusters: Each country is assigned to a cluster based on the similarity of its time series to those of other countries.

To determine the optimal number of clusters, different methods can be used. In this study, the silhouette method is applied, which evaluates clustering quality by measuring how well each cluster is separated from the others. A score close to 1 indicates well-defined clusters, whereas a score near 0 suggests overlapping groups. Values of k that yield a silhouette score close to 1 are examined to select an appropriate number of clusters.

Once the k clusters are formed, each represents a group of countries with similar patterns in the evolution of the corresponding SDG index.

Clustering process using the dynamic time warping distance between time series. The DTW distance is a metric designed to measure the similarity between two time series that may be misaligned in time. Unlike the Euclidean distance, DTW allows for nonlinear alignment between the series by finding the best match between their points, enabling "stretching" and "compression" of the series.

For example, two series with similar patterns but shifted in time (such as a country improving earlier than another) may have a small DTW distance, whereas their Euclidean distance could be large. Unlike the Euclidean method, which directly compares each point in one series with the corresponding point in another, DTW searches for the "closest matching point" between the two series (see **Figure 1**). This feature allows it to identify similar shapes even if they are distorted or shifted in time.

Thus, DTW distance offers the advantage of flexible temporal alignment, allowing comparison of series with similar patterns that occur at different times. However, this comes at the cost of higher computational complexity. The clustering process using DTW distance is identical to the process using Euclidean distance, with the only difference being the substitution of one distance measure for the other.

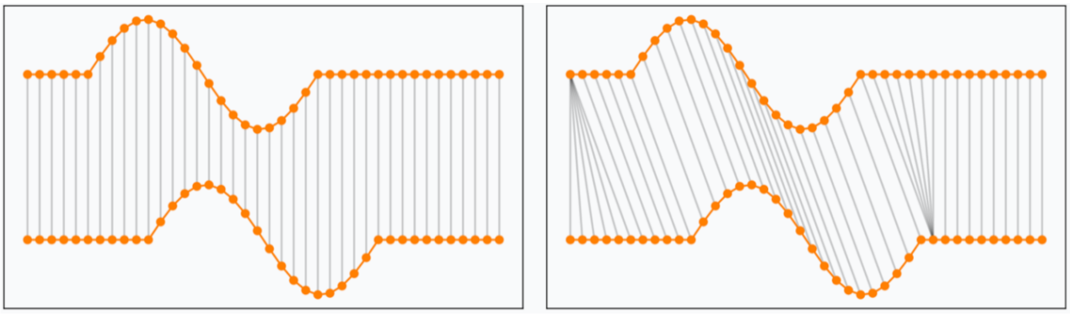


Figure 1. Comparison between Euclidean distance (left) and DTW (right), source: [24]

Vector Autoregressive Model Analysis

Given a time series of the SDG indices (2, 6, 7, and 15) for the EU or an individual EU country, the objective is to estimate a VAR(p) model to analyse the relationships between these four SDGs. Specifically, the aim is to determine whether past values of one SDG index influence its own evolution and the evolution of the other SDG indices.

The VAR(p) model is a statistical framework for analysing and predicting interactions among multiple dependent variables in time series data. In this case, the four time series correspond to the SDG indices (2, 6, 7, and 15).

The VAR(p) model assumes that each variable y_t in the system is influenced by the following features: 1) Its own lagged values up to order *p*; 2) The lagged values of the other variables in the system up to the same order *p*.

The general equation for a VAR(p) system with *k* variables is:

$$\boldsymbol{y_t} = c + A_1\boldsymbol{y_{t-1}} + A_2\boldsymbol{y_{t-2}} + \cdots + A_p\boldsymbol{y_{t-p}} + \epsilon_t \qquad (2)$$

where: $\boldsymbol{y_t}$ is a vector containing the *k* variables at time *t* (in this case, the SDG indices at *t*); *c* is a vector of constant terms; A_1, A_2,..., A_p are coefficient matrices that indicate how past values of the variables influence the system; and ϵ_t is a vector of error terms.

In the context of the SDGs, a VAR(p) model can help address questions such as:

- Does past progress in SDG 2 influence improvements or declines in SDG 6 in the present?
- Are there reciprocal interactions between different SDGs?

However, certain conditions must be met to apply a VAR(p) model:

1. Stationarity of the time series. The series must be stationary (i.e., have constant mean and variance over time). If they are not, transformations, such as logarithms and differencing, can be applied. The Augmented Dickey-Fuller (ADF) test will be used to assess stationarity.
2. Number of observations and lag selection. With only 24 observations, the model can still be used if the number of lags p is limited. The optimal lag order p will be determined using the AIC(n), HQ(n), SC(n), and FPE(n) criteria [21].
3. Correlation among the time series. The model is meaningful only if the correlations are significant. The Granger Causality Test will be used to assess these relationships.

When the conditions are met, the VAR(p) model is a powerful tool for analysing interactions among SDGs. It enables an assessment of whether progress in one SDG (e.g., Clean Water and Sanitation) is linked to changes in other goals (e.g., Zero Hunger or Life on Land). This insight can provide valuable guidance for developing more integrated policy strategies.

RESULTS

The results from both the clustering process and the VAR(p) model were obtained using R codes.

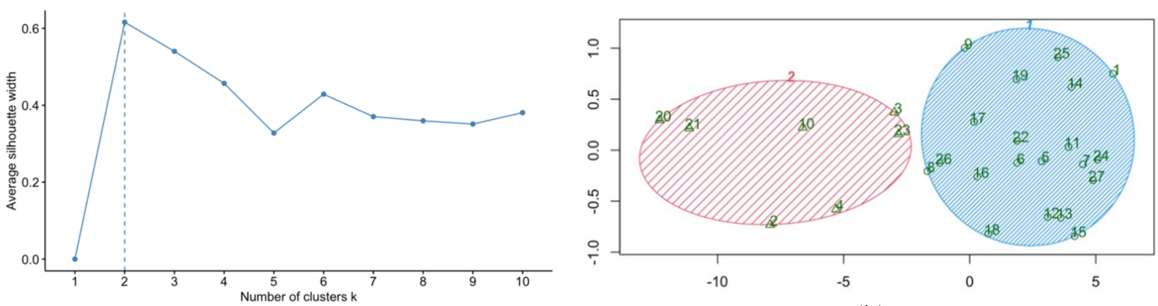
Clustering Outcome

The analysis begins with the Euclidean distance. As shown in **Figure 2a**, the optimal number of clusters for the SDG 2 indices across the 27 EU countries, determined using the silhouette method, is 2. Additionally, in **Figure 2b**, the clusplot function in R software is used to visualise the clustering results, applying the *k*-means algorithm for SDG 2.

For SDGs 6 and 15, 3 clusters are considered, while for SDG 7, 4 are considered. Notably, in all four SDG cases, the percentage of total data variability explained by differences between clusters exceeds 70%. This situation indicates that a significant portion of the data's variability stems from differences among the groups identified by the k-means algorithm, suggesting that the model has effectively achieved clear separation between the clusters. **Table 1** shows the countries assigned to each cluster for SDGs 2, 6, 7, and 15.

The countries in the green cluster have a higher average than those in the yellow cluster, which in turn have a higher average than those in the orange cluster, followed by the red cluster with the lowest values. These colours are utilised later to compare them with the colour classifications assigned in [18] for the different countries: Green = Goal Achieved, Yellow = Challenges Remain, Orange = Significant Challenges, and Red = Major Challenges.

Next, the clustering process is repeated for the 27 EU countries for SDGs 2, 6, 7, and 15, using Dynamic Time Warping distance instead of Euclidean distance. The results are presented in **Table 2**.



(a) (b)

Figure 2. Number of clusters for SDG 2 (a), clustering of EU countries for SDG 2 using Euclidean distance (b); source: own elaboration

Table 1. Clustering of EU countries using Euclidean distance

	SDG 2	SDG 6	SDG 7	SDG 15
Green			1,10,27	
Yellow		1,5,6,7,8,10,11 12,18,21,22,25,27	5,6,7,8,9,11,13, 19,26	7,9,17,19
Orange	1,5,6,7,8,9,11,12, 13,14,15,16,17, 18,19,22,24,25, 26,27	2,3,9,13,14,15,16, 17,19,23,26	2,12,14,15,16,20, 21,22,23,24,25	2,3,5,10,14,15, 16,22,25,26,27
Red	2,3,4,10, 20,21,23	4,20,24	3,4,17,18	1,4,6,8,11,12,13, 18,20,21,23,24

Table 2. Clustering of EU countries using the DTW distance

	SDG 2	SDG 6	SDG 7	SDG 15
Green			1,7,10,26,27	
Yellow		1,5,6,7,8,10,11, 12,21,27	2,5,6,8,9,11,13, 14,15,16,19,21, 23,25	3,5,7,9,10,13, 14,15,17,19, 22,25,26
Orange	1,5,6,7,9,11,12, 13,14,15,16,17,18,19, 22,24,26,27	2,9,13,14,16,18, 19,22,25,26	12,17,18,20	1,2,4,6,12,16, 21,23,24,27
Red	2,3,4,8,10,20,21,23, 25	3,4,15,17,20,23,24	3,4,22,24	8,11,18,20

A comparison of the colour associations of countries in [18] with the results in Table 1 and Table 2 reveals that the countries sharing the same colours across all three cases are as follows:

For SDG 2, Orange: Austria, Czech Republic, Denmark, Greece, Croatia, Ireland, Luxembourg, Poland, Romania, Slovenia, Sweden; Red: Cyprus, Finland, Malta, Netherlands.

For SDG 6, Yellow: Austria, Czech Republic, Germany, Denmark, Spain, Finland, France, Greece, Netherlands, Sweden; Orange: Belgium, Estonia, Croatia, Italy, Latvia, Slovenia; Red: Cyprus, Malta.

For SDG 7, Green: Austria, Finland, Sweden; Yellow: Germany, Croatia, Latvia; Orange: Greece, Malta.

For SDG 15, Yellow: Denmark, Estonia, Lithuania, Latvia; Orange: Belgium; Red: Spain, France, Luxembourg, Malta.

The relevance of this comparison lies in the fact that the three clustering approaches are based on different types of information. While [18] groups countries according to the values of the SDG indices in a single year, the present study considers the temporal evolution of these indices over 2001–2023. Moreover, two different distance measures are applied to the time series (Euclidean distance and Dynamic Time Warping), which capture similarity in different ways.

The presence of countries that remain in the same cluster across all three approaches, therefore, suggests that these countries exhibit similar levels of performance and comparable development trajectories in the SDG indicators related to the WEFE nexus. This consistency indicates that the observed similarities between countries reflect structural characteristics of their sustainability performance rather than being driven by the specific methodological approach used.

Conversely, cases in which countries change clusters across methods may reveal differences between static performance and dynamic evolution. Such discrepancies can indicate countries with similar current SDG levels but different development trajectories over time, or countries following similar trends despite differences in their absolute performance levels.

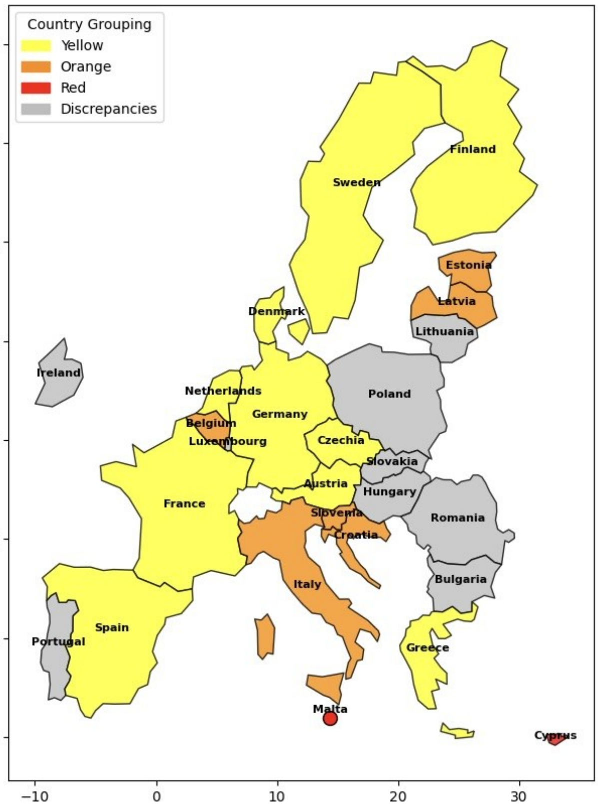


Figure 3. European Union–categorisation by affinity and discrepancies;
source: own elaboration

In our case, it is worth noting that, based on the number of matches across the three cases, the grouping of countries by colour according to their progress in achieving the respective SDGs [18] closely resembles the grouping obtained from the time series using the two distance measures considered. Figure 3 presents a map of Europe for SDG 6, showing countries that belong to the same group across all three metrics in yellow, orange, and red. In contrast, countries with discrepancies across metrics are displayed in grey. Figure 4 includes a Sankey diagram illustrating the flows between colours. In particular, flows between different colours are scarce, especially between the clusters derived from the Euclidean metric and those reported in [18].

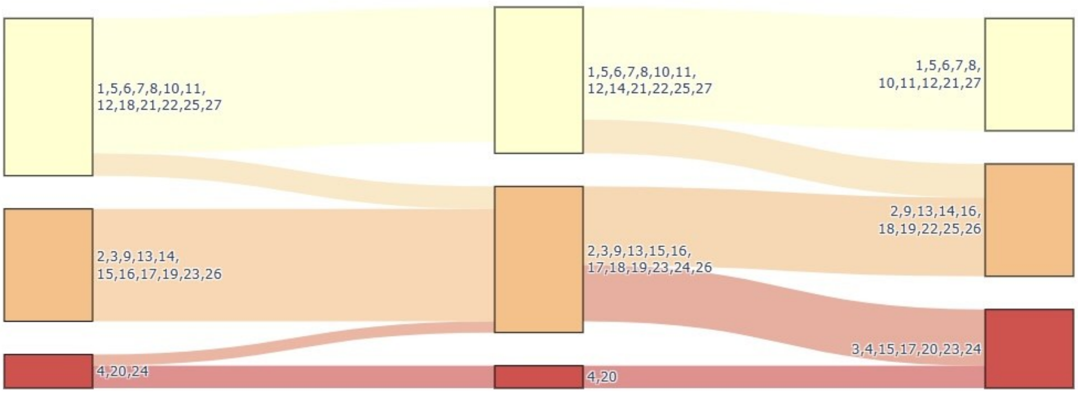
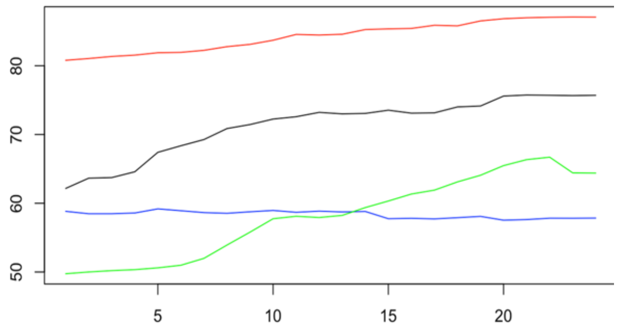


Figure 4. Country transitions between clusters with respect to SDG6 behaviour: Euclidean (left),reported in [18] (centre), and DTW (right); source: own elaboration

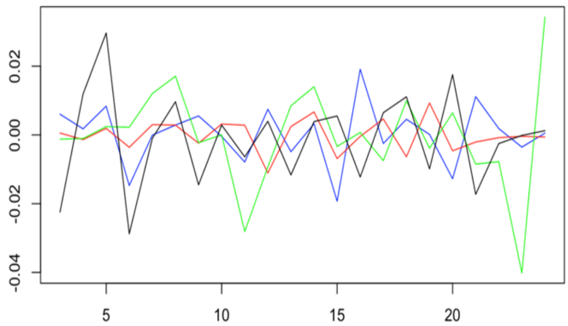
Vector Autoregressive Model Analysis results

In the previous section, the twenty-seven EU countries were grouped into clusters using two different distance measures. In this section, the time series of the SDG indices (2, 6, 7, and 15) for the EU as a whole and for different EU countries are utilised, based on the clusters obtained earlier. The objective is to apply a VAR(p) model to analyse the relationship between the four SDGs.

Figure 5a presents the time series representation of SDGs 2, 6, 7, and 15 at the EU level. After transforming the four time series to logarithms, the ndiffs function in R software is used to determine the optimal number of differences needed to achieve stationarity. In our case, this number is 2. **Figure 5b** shows the representation of the four resulting time series after applying second-order differencing to the logarithm-transformed original series.



(a)



(b)

Figure 5. Evolution of the four SDGs (2 in blue, 6 in red, 7 in green, and 15 in black) in the EU since the year 2000 (a), transformed time series (b); source: own elaboration

The augmented Dickey-Fuller test confirms that the four series in **Figure 5b** are stationary, meaning that their statistical properties (such as mean and variance) remain constant over time. However, the stationarity of the SDG 2, 7, and 15 series is confirmed with a confidence level well below 0.05, while for the SDG 7 series, the confidence level is slightly above 0.05. The optimal number of lags is 2, and the Granger causality test indicates that some variables are influenced by their lags. The results of the VAR models for each SDG are shown below.

Model for SDG 2:

$$\begin{aligned} \boldsymbol{SDG2_t} = &-0.563970\boldsymbol{SDG2_{t-1}} - 1.539703\boldsymbol{SDG6_{t-1}} - 0.120420\boldsymbol{SDG7_{t-1}} + \\ &0.076858\,\boldsymbol{SDG15_{t-1}} - 0.072500\boldsymbol{SDG2_{t-2}} - 0.772055\boldsymbol{SDS6_{t-2}} + \\ &0.49334\boldsymbol{SDG7_{t-2}} - 0.218953\boldsymbol{SDG15_{t-2}} - 0.000882 \end{aligned} \tag{3}$$

Model for SDG 6:

$$\begin{aligned} \boldsymbol{SDG6_t} = &\ 0.01399\boldsymbol{SDG2_{t-1}} - 0.93867\boldsymbol{SDG6_{t-1}} + 0.15326\,\boldsymbol{SDG7_{t-1}} \\ &- 0.03720\boldsymbol{SDG15_{t-1}} + 0.06211\,\boldsymbol{SDG2_{t-2}} - 0.65778\boldsymbol{SDG6_{t-2}} \\ &+ 0.03405\boldsymbol{SDG7_{t-2}} - 0.04470\boldsymbol{SDG15_{t-2}} - 0.00015 \end{aligned} \tag{4}$$

Model for SDG 7:

$$\begin{aligned} \boldsymbol{SDG7_t} = &-0.800080\boldsymbol{SDG2_{t-1}} + 0.047244\,\boldsymbol{SDG6_{t-1}} - \\ &0.217641\boldsymbol{SDG7_{t-1}} + 0.270293\boldsymbol{SDG15_{t-1}} - 0.519623\boldsymbol{SDG2_{t-2}} - \\ &1.072640\boldsymbol{SDG6_{t-2}} - 0.042261\boldsymbol{SDG7_{t-2}} + 0.245272\boldsymbol{SDG15_{t-2}} - 0.000142 \end{aligned} \tag{5}$$

Model for SDG 15:

$$\boldsymbol{SDG15_t} = 0.24605\boldsymbol{SDG2_{t-1}} + 0.32781\,\boldsymbol{SDG6_{t-1}} - 0.13313\,\boldsymbol{SDG7_{t-1}} - 0.60559\,\boldsymbol{SDG15_{t-1}} + 0.28004\boldsymbol{SDG2_{t-2}} - 0.24447\boldsymbol{SDG6_{t-2}} + 0.23784\boldsymbol{SDG7_{t-2}} - 0.55870\,\boldsymbol{SDG15_{t-2}} - 0.00173 \quad (6)$$

Each equation describes the temporal evolution of one of the series (SDG 2, SDG 6, SDG 7, and SDG 15) based on its own lags (*t*–1 and *t*–2) and the lags of the other series. The coefficients of each lag term indicate the impact of each series on the dependent series at the current time.

The SDG 6 and SDG 15 series exhibit a strong dependence on their own lags. This characteristic implies that these series exhibit little variability or abrupt changes, with past effects persisting for a significant period. The interactions between the series are notable, particularly with SDG 6, which has a considerable negative impact on SDG 2 and SDG 7. These relationships suggest that changes in SDG 6 directly affect the other series, positioning it as a key driver within the time-series system, as it significantly influences the other elements in the model.

This dynamic structure demonstrates that the VAR model is well-suited to capturing the temporal interdependence between the series. It provides insight into how the variables evolve together, depending on both their past values and their interactions.

Next, the same Vector Autoregressive method is applied to five European countries whose situations differ in relation to the clustering processes performed.

First, Malta is considered to be among the countries in the red group for almost all four SDGs. For Malta, the model suggests using three lags. SDG 6 presents the most negative coefficients for its lags (−1.32 in the first lag). Regarding the variables that most affect the others, SDG 6 has a negative impact on SDG 2 (−0.87 and −0.96). SDG 2 has a significant impact on SDG 7 (1.02 in the second lag) and SDG 15 (0.6 in the third lag).

In the case of Austria, a country with very good results in SDGs 2, 6, and 7 but relatively poor performance in SDG 15, the model also suggests using three lags. In this case, SDGs 2 and 6 are strongly influenced by their own lags. SDG 2 presents coefficients of –0.51611 for the first lag and –0.58341 for the second, while SDG 6 presents coefficients of –0.775143 for the first lag and –0.828325 for the second. SDG 7 is predominantly affected by SDG 6 (3.7 in the second lag) and SDG 15 (1.28 in the first lag and 1.81 in the second). SDG 15 exhibits a balance between self-influence and the influence of other variables, particularly SDG 6 (0.75 in the second lag).

For Finland, a country with very good results in SDGs 6, 7, and 15 but weaker performance in SDG 2, the model suggests using two lags. SDG 6 has a strong influence on SDG 7, especially in the second lag, with a coefficient of −1.92. SDG 6 also significantly influences SDG 15, with a coefficient of 1.62. SDG 2 shows self-influence in its own lags, with coefficients of –0.603 in the first lag and −0.289 in the second.

Croatia shows acceptable results in all four SDGs. SDG 6 has a strong negative impact on SDG 2 (coefficient −2.626 in the first lag), on itself (–0.920 in the first lag), and on SDG 15 (−3.311 in the first lag), with persistent effects across the lags.

Finally, Spain, a country with acceptable results in SDGs 6 and 7 but moderate performance in SDGs 2 and 15, presents a negative impact of SDG 2 on SDG 7, with a coefficient of –0.9625. There is also a negative impact of SDG 6 on itself (–0.9157) and of SDG 7 on itself (–0.6529) (all previous coefficients correspond to the first lag). Additionally, SDG 2 influences itself negatively (–0.5507 in the first lag and –0.6684 in the second lag). Other impacts are more moderate, with coefficients below 0.5.

DISCUSSION

The results obtained from the clustering analysis and the VAR(p) models provide empirical evidence on the functioning of the Water-Energy-Food=Ecosystem (WEFE) nexus within the European Union. By combining time-series clustering with dynamic modelling, the study captures both structural similarities across countries and temporal interdependencies among the Sustainable Development Goals (SDGs), which represent the different components of the nexus.

The clustering analysis reveals clear patterns in the evolution of SDG indicators across EU member states. Using Euclidean distance, the optimal number of clusters is two for SDG 2, three for SDGs 6 and 15, and four for SDG 7, with more than 70% of the total variability explained by differences between clusters. This indicates that the clustering algorithm successfully identifies meaningful groupings of countries based on their SDG trajectories.

When the clustering process is repeated using the Dynamic Time Warping (DTW) distance, the resulting groups remain largely consistent with those obtained using Euclidean distance. The comparison with the colour classification provided in the European Sustainable Development Report shows a high degree of correspondence between the clusters derived from the time-series analysis and the SDG performance categories reported in the literature. In particular, several countries appear consistently within the same groups across the three classifications. For instance, Austria, Finland, and Sweden appear in the green cluster for SDG 7, while Cyprus and Malta consistently appear in the red cluster for SDG 6. This approach therefore provides a dynamic perspective on sustainability progress, allowing the identification of groups of countries that share similar development paths.

The VAR(p) results reveal significant dynamic relationships between the four SDGs considered in the analysis. At the EU level, the model for SDG 2 shows relatively strong negative effects from SDG 6. This result suggests that changes in water management may have important short-term impacts on food security. From a policy perspective, it underscores the need to design agricultural policies that integrate sustainable water management practices, such as efficient irrigation systems, water reuse, and climate-smart agriculture. It also underscores the importance of coordinating agricultural and water resource policies to prevent water restrictions or shocks from negatively affecting food production.

The positive coefficient for SDG 7 at lag 2 for SDG 2 indicates that improvements in sustainable energy systems can benefit food security with a certain delay. This result supports policies that promote renewable energy in the agricultural sector, such as solar energy for irrigation, rural electrification, and improved energy efficiency in agri-food supply chains. Investment in energy technologies that reduce production costs and increase the resilience of agricultural systems may therefore generate positive spillovers for food security.

The SDG 7 model also shows negative effects from SDG 2 in both lags. This relationship may reflect tensions between agricultural expansion and sustainable energy objectives. Policies encouraging land-intensive agricultural production or bioenergy development may compete with energy transition strategies. For this reason, policy design should avoid measures that promote land-intensive energy uses that compete with food production, while instead supporting second-generation bioenergy and energy efficiency strategies that minimise conflicts between agriculture and energy systems.

The model for SDG 15 shows positive short-term effects of water management, indicating that improvements in water resources can favour terrestrial ecosystems. This finding supports policies aimed at restoring aquatic ecosystems and protecting river basins. Integrating biodiversity policies with water and land-use planning can therefore contribute to strengthening ecosystem sustainability within the WEFE nexus.

In addition, the negative coefficients of the own lags observed in several models suggest the presence of correction or adjustment dynamics. These results indicate that shocks affecting the SDGs may gradually dissipate over time, although they can also generate instability if policies across sectors are not properly coordinated. This situation highlights the importance of implementing cross-sectoral SDG strategies and strengthening coordination mechanisms between agricultural, water, energy, and biodiversity policies at the European level. Overall, the VAR results at the EU level suggest that the most effective policies for the analysed SDGs are those that integrate natural resources, energy systems, and agricultural production, reducing trade-offs and exploiting synergies across sectors.

Although these results provide a general policy framework for the European Union, the country-level models reveal important differences in how these interactions operate across member states. For example, in Austria, SDG 6 strongly influences both SDG 7 and SDG 15. This pattern is consistent with the European policy recommendation of integrating water management, energy systems, and ecosystem protection. In Finland, water management (SDG 6) strongly influences biodiversity (SDG 15), while a negative effect of SDG 6 on SDG 7 suggests potential tensions between water and energy policies. This result is broadly consistent with European environmental policies that emphasise ecosystem protection through water management while recognising possible trade-offs with energy transitions.

In the case of Spain, the model mainly shows internal adjustment dynamics, reflected in the negative self-influence of several SDGs. In addition, the negative effect of SDG 2 on SDG 7 is consistent with the pattern observed at the EU level. For Malta, the model shows that SDG 6 has negative effects on SDG 2, which is consistent with the negative relationship identified at the European level, though the effect is considerably stronger. However, unlike the EU results, SDG 2 has a positive influence on energy in Malta. Finally, in the case of Croatia, water management has very strong negative effects on SDG 2 and SDG 15. While the negative impact on SDG 2 is consistent with the EU results, the negative relationship with SDG 15 differs from the European pattern. Therefore, the synergies observed at the EU level between water management and ecosystem outcomes are not replicated in this case.

These differences suggest that some policies that are beneficial at the EU level may generate challenges in specific national contexts. For example, strict water management regulations aimed at protecting ecosystems could generate positive environmental outcomes at the European scale but produce adverse effects in countries such as Croatia, where water restrictions may negatively affect both food production and ecosystem indicators. In general, the countries most aligned with the European dynamics are Austria and, to a lesser extent, Spain and Finland, while Malta and Croatia show more divergent patterns. This suggests that EU sustainability policies should maintain an integrated nexus perspective while allowing for national-level adaptations.

Although no previous studies have analysed the WEFE or WEF nexus in the European Union using autoregressive models applied to SDG indicators, our VAR model, which identifies temporal spillovers between sustainability performance indicators represented by SDGs, can be compared with other econometric approaches used in the literature. In particular, a Structural Vector Autoregression (SVAR) model, which focuses on structural relationships between physical production variables, and a Panel Vector Autoregression (PVAR) model, which captures dynamic interactions across regions and identifies broader socio-economic drivers, have been applied to the analysis of the nexus in China in [7] and [15], respectively.

Despite these methodological differences and the different geographical contexts in which the models are applied, several similarities emerge. The behaviour of SDG 2 and SDG 7 is consistent across the three modelling approaches. In contrast, the relationship between SDG 2 and SDG 6 in our VAR model is similar to that in the SVAR model but differs from the PVAR results. In contrast, the opposite holds for the relationship between SDG 6 and SDG 7.

The PVAR analysis also examines the relationship between SDG 2 and SDG 15, which is consistent with our results. The interactions between SDG 15 and SDG 7 are also very similar in both models. In addition, the influence of SDG 6 on SDG 15 is positive in both approaches, although the influence of SDG 15 on SDG 7 differs between the models. Overall, these results converge on similar conclusions: the WEFE nexus is characterised by complex interdependencies, and effective policy design must account for these interactions in order to avoid unintended consequences.

CONCLUSION

This study combines an unsupervised machine learning technique (clustering) with a multivariate time-series model VAR(p) to analyse the evolution and interactions of selected Sustainable Development Goals in the European Union. Specifically, the analysis focuses on SDG 2 (food systems), SDG 6 (water resources), SDG 7 (energy systems), and SDG 15 (terrestrial ecosystems), which represent key dimensions of the Water–Energy–Food–Ecosystem (WEFE) nexus. By examining both the trajectories of these indicators and their dynamic interactions, the study contributes to understanding how progress in one sustainability dimension may influence others across the EU and within individual member states.

The clustering analysis provides a first descriptive perspective on how countries evolve in relation to these SDGs. Using both Euclidean and Dynamic Time Warping (DTW) distances, the clustering results show high consistency across methods, with most countries belonging to the same cluster regardless of the distance measure applied. Differences between methods are minimal and mainly occur for a few countries in the case of SDG 15. This consistency suggests that the clustering results are robust and can be used as a reliable tool for monitoring sustainability progress across countries. From a policy perspective, this classification can support benchmarking exercises within the EU by identifying groups of countries with similar trajectories in WEFE-related indicators, facilitating the exchange of best practices and improving the monitoring of sustainability targets.

Beyond this descriptive classification, the VAR model provides insights into the dynamic relationships between the selected SDGs. By incorporating lagged variables, the model captures how changes in one sustainability dimension may propagate over time to others. The presence of effects in the first lag reflects relatively immediate responses, while effects appearing in later lags indicate more gradual adjustments within the system. In practical terms, this means that improvements or shocks affecting one sector of the nexus may influence other sectors with a time delay.

The empirical results confirm the existence of strong interdependencies between the selected SDGs, particularly highlighting the role of water-related indicators in shaping outcomes in food and energy systems. In addition, some variables, especially SDG 6 and SDG 15, show strong persistence through their own lagged values, suggesting that progress in these areas tends to evolve gradually over time. At the same time, the analysis reveals that these interactions are not uniform across countries. While the EU-level model identifies general patterns in nexus dynamics, country-level estimations show that the strength and direction of relationships can vary significantly across member states. This finding suggests that EU-level sustainability strategies should be complemented by national-level adaptations that take into account country-specific conditions.

From a practical perspective, the VAR framework can also support policy analysis by serving as a forecasting tool. The estimated relationships can be used to simulate how changes in a particular indicator, such as improvements in water management or energy systems, may influence other sustainability outcomes over time. Such simulations can help policymakers anticipate potential trade-offs or synergies between sectors and design more coordinated strategies within the WEFE nexus.

Despite the contributions of this study, several limitations should be acknowledged. First, the analysis focuses on a limited set of SDGs associated with the WEFE nexus. Expanding the analysis to include additional SDGs related to environmental sustainability and resource management could provide a more comprehensive view of nexus interactions. However, incorporating a larger number of variables would require longer time series with more years of data to ensure robust model estimation. Second, the study relies on a standard VAR framework, which captures dynamic interactions between variables but does not explicitly identify structural causal mechanisms or cross-country dependencies. Future research could therefore extend the analysis by applying alternative approaches such as Structural VAR (SVAR) or Panel VAR (PVAR) models. These extensions would provide complementary insights into the functioning of the WEFE nexus and help refine the evidence base for integrated sustainability policymaking in the European Union.

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DATA AVAILABILITY STATEMENT

The data on the SDG indicators, as well as the R codes used for the clustering procedures and the implementation of the VAR(p) model, are available upon request for interested researchers.

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