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The Use of Renewable Energy Sources and Environmental Degradation in EU Countries

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Abstract: Renewable energy sources play a crucial role in sustainable development strategies, addressing environmental protection, energy security, economic growth, and enhancing quality of life. Renewable energy sources are significantly less damaging to the environment compared to traditional energy sources, as they help lower greenhouse gas emissions, decrease air and water pollution, and consequently, limit environmental degradation. The study helped formulate the following research goals: assessment of changes in the use of renewable energy sources and the degree of environmental degradation in the European Union countries, and comparison of the spatial differentiation of the EU countries in terms of the use of renewable energy sources and the degree of environmental degradation, taking into account both indicated criteria. The survey covers the years 2015, 2019, and 2021. The article highlights the important role of analytical methods in the analysis of renewable energy consumption and its impact on the environment. The Self-Organizing Map was used for grouping the European Union countries based on renewable energy sources' levels and environmental degradation, allowing the identification of patterns and clusters. The results showed that the Scandinavian countries are leading the way in renewable energy sources and low environmental degradation, while the Eastern European countries are struggling, with a low share of renewable energy sources and high degradation.

Keywords: renewable energy sources; environmental degradation; the Self-Organizing Map; EU countries; grouping

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1. Introduction

Renewable energy sources (RES) are becoming increasingly vital in the global energy system. In the face of challenges, such as climate change and its effects, rising energy costs, and depletion of fossil fuel resources, RES are becoming a key element of the energy transformation. Rising economic activity is driving up energy demand, primarily met by conventional sources. This increased consumption of traditional energy has a negative effect on the environment. Therefore, the attention of policymakers has shifted toward promoting renewable energy production and its use in various types of economic activities in order to ensure a low-emission economy [1]. RES are natural, repeatable natural processes that allow for the generation of energy as an alternative to fossil fuels. These sources, unlike non-renewable ones, are inexhaustible and environmentally friendly. Widespread adoption of these sources will lower greenhouse gas emissions, decrease waste generated in energy production, and likely enhance global energy security [2]. The most important types are solar energy, wind energy, hydropower, geothermal energy, and biomass energy [3]. Each type of renewable energy has its own unique characteristics and carries certain risks that all interested parties should carefully evaluate before deciding to invest in a project [4]. For example, interesting considerations on the use of wind energy can be found in [5–7].

There is a close relationship between RES and environmental degradation, and RES are a key tool in combating the negative effects of RES environmental degradation. Environmental degradation has a multifaceted impact on countries around the world, adversely affecting their environment, society, and economy. At the same time, low human development and high population growth increase environmental degradation [8]. Environmental protection and combating climate change are currently among the most important global challenges. Awareness of the threats resulting from environmental degradation has contributed to the ongoing energy transformation process in the global economy, in which RES replacing conventional sources and low-emission technologies play a significant role [9–12]. RES help reduce the negative effects of environmental degradation because they contribute to reducing CO_2 emissions, protecting natural resources, and reducing pollution. The use of renewable energy supports sustainable socioeconomic development by contributing to reducing its negative impact on the environment.

In the study, to assess the European Union's (EU) policy on renewable energy and environmental degradation, we use the Self-Organizing Map (SOM) method, which allows us to identify groups of countries similar in terms of the use of renewable energy and the degree of environmental degradation.

The study established the following research objectives:

- Assessment of changes in the use of renewable energy and the degree of environmental degradation in EU countries.
- Identification of countries with similar use of renewable energy and the degree of environmental degradation.

To achieve our research objectives, we refer to information contained in the Eurostat Database and TheGlobalEconomy.com, indicating the use of renewable energy and the degree of environmental degradation in the EU countries in 2015, 2019, and 2021.

The innovative nature of our study is associated with the use of artificial neural networks, which allow us to obtain a comprehensive picture of the changes taking place in the EU countries. The use of the SOM to group countries allows the identification of important patterns and trends that support the EU's efforts to achieve climate neutrality. This provides a better understanding of how the EU's policies translate into the actual progress of countries in the area of sustainable development. Our study fills the gap in research on the use of RES and the degree of environmental degradation and allows us to identify changes in the EU countries thanks to the analysis of both unidimensional and multidimensional indicators characterizing the studied phenomenon.

The structure of this paper is organized as follows: the introduction presents the primary research objectives and the motivations behind the study. Section 2 offers a literature review, addressing the extent of environmental degradation, the utilization of renewable energy sources (RES), and the application of artificial neural networks in environmental studies. Section 3 discusses the data and research methods used. Section 4 provides a detailed account of the research results. Finally, the paper concludes with a discussion and summary of key findings.

2. Literature Review

2.1. Environmental Degradation

The process of environmental degradation is the deterioration of natural resources and ecosystems, leading to their damage or destruction [13,14]. Its main cause is human activity, which, by producing and managing goods, disrupts the self-regulating mechanisms of the natural environment and its natural structure. Industry, transport, burning of fossil fuels, inadequate waste management, increasing urbanization and industrialization, deforestation, overgrazing of animals and cultivation of crops, and improper water management lead to air, soil, and water pollution.

Worldwide, air pollution is the greatest environmental health threat, causing cardiovascular, respiratory, and nervous system diseases that impair the quality of life of people of all ages [15–17]. The particulate matter up to 2.5 μm (PM2.5) and 10 μm (PM10) in diameter, tro-

pospheric ozone (O_3), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), carbon monoxide (CO), benzo[a]pyrene (BaP), benzene (C_6H_6), and toxic metals, such as arsenic (As), cadmium (Cd), lead (Pb), and nickel (Ni), are the main sources of air pollution. Fine particulate matter (PM2.5), which originates primarily from human activities related to the burning of fossil fuels, causes the most serious health effects, leading to deaths [15,18–21]. In addition, even short-term exposure to PM2.5 air pollution may contribute to the faster spread of infectious diseases (including COVID-19) and increased mortality in their aftermath [17,22,23].

In order to protect the population from the adverse effects of exposure to air pollutants, the World Health Organization (WHO) has set its global limits, above which an alert is issued. From 2021, the average concentration of PM2.5 can be a maximum of 15 $\mu g/m^3$ per day and 5 $\mu g/m^3$ per year [20]. Despite this, according to the WHO data, 99% of the world's population breathes air with pollutant concentrations above the set limits. The most exposed populations are those of low- and middle-income countries, which at the same time contribute less to the production of these pollutants. The standards in force in the EU countries, as set out in the Ambient Air Quality Directives 2004/107/EC and 2008/50/EC, are less stringent than those set by the WHO [24]. According to the European Environment Agency, in 2022, 96% of urban dwellers in the EU were exposed to PM2.5 concentrations above the WHO limits, whereas according to the EU standards (annual limit value of 25 $\mu g/m^3$), the percentage was less than 1% [15]. The need to align the EU's air quality standards with the latest WHO recommendations, as well as real reductions in air pollution and improvements in air quality, were addressed in 2019 in the European Green Deal [25], but it was not until 2024 that the European Council presidency and European Parliament decided to align the limits with the WHO recommendations to achieve the goal of zero emissions and a non-toxic environment in the EU in 2050 [26]. In this study, the grouping of EU countries allows us to assess whether the objectives of the European Green Deal are being realized in the EU countries, which are grouped according to the degree of environmental degradation and the use of RES.

Some of the air pollutants listed above are also among the greenhouse gases involved in the greenhouse effect. The presence of greenhouse gases in the atmosphere is essential for sustaining life. Without them, the Earth's surface temperature would be approximately 33 °C lower, with an average temperature of −18 °C [27,28]. However, excess greenhouse gases in the atmosphere are harmful, as they cause global warming characterized by a progressive increase in the Earth's average temperature. As defined by the 1992 United Nations Framework Convention on Climate Change, greenhouse gases are the gaseous constituents of the atmosphere, whether of natural or anthropogenic origin, that have the capacity to absorb and re-emit infrared radiation [29]. According to the 1997 Kyoto Protocol, these include three gases, both naturally occurring in the atmosphere and generated by human activities: carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O), as well as four fluorinated gases produced by man and used in industry, which have up to several thousand times the greenhouse potential of CO_2: hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), sulfur hexafluoride (SF_6), and nitrogen trifluoride (NF_3) [30]. The Kyoto Protocol did not include water vapor in the set of greenhouse gases. Its lifetime in the atmosphere is too short to control the planet's temperature on its own. Water vapor does not cause global warming, but is a consequence of it, and when it increases in the atmosphere, it amplifies the effects of other greenhouse gases [28]. The main sources of increased greenhouse gases in the atmosphere are energy production, fossil fuel and solid waste combustion, coal, natural gas and oil production, transport, industry, construction, chemical production, agriculture, forestry, and fisheries [31,32]. In 2019, more than 77% of the EU's total greenhouse gas emissions came from the energy sector. Greenhouse gases have different greenhouse effect potentials, so their impact is converted into CO_2 equivalents, allowing the determination of the carbon footprint [31,33–35]. In 2021, greenhouse gas emissions generated by the economic activities of the EU countries amounted to 3.6 billion tons of CO_2 equivalent, of which 80% of the volume was CO_2. The EU's share of global

emissions at that time was 7.3%, being one of the largest shares in the world after those of China and the United States [36,37].

Greenhouse gases remain in the atmosphere for a period of several to even several thousand years. They contribute to global warming by affecting the climate worldwide, regardless of where they are emitted. Average temperatures grow, rainfall and snowfall patterns change, and extreme weather events occur, such as heat waves, droughts, and floods. Environmental changes are taking place, such as sea level rise and acidification, degradation of forests and coastal areas, changes in habitats and wildlife populations, and reductions in biodiversity. The economies of countries are also negatively impacted by climate change. Climate change affects human health by causing respiratory diseases, heat stress, and increased prevalence of infectious diseases, especially in African countries [38,39]. Progressive global warming is anthropogenic, i.e., caused by human activity. Since the pre-industrial era, there has been an increase in the global surface temperature of more than 1 °C and, in the absence of decisive action, it could increase by up to 4 °C by 2100 [40]. In 2015, at the 21st United Nations Climate Change Conference in Paris, an agreement to strengthen the global response to the threat of climate change was adopted to replace the Kyoto Protocol. It resolved to reduce greenhouse gas emissions to such an extent as to limit the increase in the Earth's surface temperature to 1.5 °C above the pre-industrial levels. The EU Council approved the Paris Agreement on behalf of the Union in 2016 [41]. The agreement aims to achieve at least a 40% reduction in economy-wide greenhouse gas emissions by 2030 compared to 1990. In 2019, the European Green Deal set a target of reducing greenhouse gas emissions by 90% by 2050 compared to 1990 levels to achieve the goal of climate neutrality [25]. Climate neutrality (neutral emissions, neutral carbon, and net-zero emissions) means a balance between all global CO_2 emissions and their absorption from the atmosphere by the so-called carbon sinks. Carbon sinks are systems that absorb more carbon dioxide than they themselves emit. As yet, there are no artificial systems that are sufficient to counteract global warming, so natural carbon sinks, such as forests, oceans, and soil, must be taken care of [42,43]. The use of renewable energy and low-carbon technologies makes it possible to receive additional carbon offsets from other sectors [10,44].

As a natural carbon sink, forests play an important role in capturing CO_2, the most common greenhouse gas. They cover 31% of the world's land area, covering 4.06 billion hectares. As much as 54% of all forests are located in just five countries: Russia, Brazil, Canada, the United States, and China. Since 1990, as a result of deforestation (i.e., the destruction of forests for other land uses), the world's forest area has decreased by 178 million ha and continues to decline. Thanks to positive trends related to afforestation and natural expansion of forests, as well as reduced deforestation, the rate of forest loss decreased in the following decades, from 1990 to 2020, amounting to, respectively, 7.8 million ha, 5.2 million ha, and 4.7 million ha [45]. Unfortunately, deforestation, agricultural expansion, and forest degradation through unsustainable logging are increasing some countries' greenhouse gas emissions—this is mainly the case in the Amazon in South America, the Congo in Africa, and countries in Southeast Asia [43,46]. Between 2015 and 2020, the highest rate of annual deforestation was recorded in Africa (4.41 million ha), followed by South America (2.95 million ha), and Asia (2.24 million ha), compared to 69,000 hectares in Europe [45]. Reduced forest cover increases the risk of floods and droughts, which is a global concern [8]. Deforestation and forest degradation, deteriorating vegetation, landslides, soil, and riverbank erosion, salinization and water contamination, deterioration of soil nutrients, but also the effects of natural disasters due to climate warming make up the process of land degradation, i.e., reduction of its productive capacity [47–49].

The degradation of land, from which almost 95% of food comes, threatens the security of the Earth's population, which the United Nations estimates to reach 10 billion by 2050. The rapid increase in the size of the population poses the challenge of providing it with more energy, water, and food. In 2012, at the Rio+20 conference, the international community adopted the UN-proposed Land Degradation Neutrality (LDN) concept, and in 2015

it was also included in the 2030 Agenda for Sustainable Development. LDN aims to ensure no net loss of healthy and productive land by preventing, reducing, and reversing land [45,50,51]. Land is also vulnerable to degradation caused by unsustainable production and consumption patterns driving demand for natural resources [52–54]. The extraction of fossil energy sources not only has an adverse impact on the environment but is also becoming increasingly difficult, as the deposits available for exploitation are depleting over time. In addition, coal-, oil-, and gas-fired power generation is a major source of CO_2 emissions worldwide [11]. The decarbonization of the EU energy system is included in the assumptions of the European Green Deal [25].

2.2. Renewable Energy Sources

The growing interest in RES first appeared in the late 1990s and was caused by the crisis triggered by the increase in oil prices, which, apart from serious financial consequences, also revealed the dependence of economies on fossil fuels [52]. During this peri-od, the world began to become increasingly aware of the problems related to environmental pollution and the main cause of this, i.e., the massive use of fossil fuels.

From 2019 to 2023, renewable energy investments increased by almost 50%, reaching USD 1.8 trillion in 2023 and growing by about 10% per year over that period. Deploying five key clean energy technologies (photovoltaics, wind, nuclear, electric vehicles, and heat pumps), between 2019 and 2023, allowed for reducing the annual fossil energy demand by about 25 EJ. This equated to 5% of the total global fossil fuel demand across all sectors in 2023, or almost the combined energy demand of Japan and South Korea from all sources last year [12].

In line with the global trend, Europe is switching to RES. The EU countries are increasing the share of all RES sources, regardless of their type, in the overall energy balance. Such actions contribute to saving natural resources, improving the environment by reducing emissions and reducing the amount of waste produced, as well as to increasing the energy security of member states [53].

The support of the governments of the member states is an essential element stimulating the development of the RES sector in the EU. Their actions should focus not only on ensuring an appropriate investment environment, e.g., in the form of financial incentives or tax relief, but also on creating an appropriate legal framework conducive to the development of this sector [54]. In the work of Bąk et al. [2], five main factors influencing the development of RES in the EU countries were identified, which include:

1. political factors, focused primarily on the aspect of policies supporting the development of RES and methods for assessing their effectiveness,
2. legal factors, relating to legal solutions directly related to the policy implemented by the state in the field of RES,
3. geographical (natural) environment, directly related to the possibilities of developing effective methods of generating energy from RES,
4. financial factors, allowing to determine the appropriate level of financing of RES-related policies, ensuring their effective operation,
5. information and education factors, reflecting the need to finance information and promotional activities, increasing the effectiveness of state policies related to RES.

The development of renewable energy technologies also has many limitations. Solangi et al. [55] identified the main types of barriers to this development as "economic and financial", "political and policy", and "market". Gajdzik et al. [56], on the basis of the literature analysis, grouped the main barriers related to the development of renewable energy into four groups of factors: administrative, political, network, and economic. The first group is related to, among others, administrative obstacles connected to the prolonged processes of obtaining permits and regulatory approvals, as well as the lack of coordination between different decision-making bodies [57]. Political barriers include, among others, unstable political support for renewable energy projects, as well as opposition from local communities and government bodies [58]. The third type of barriers are economic barriers,

linked with high capital investment costs, long payback periods [59], as well as high operational and maintenance costs. The last group of barriers are market barriers, related to issues such as problems with the market structure hindering the integration of RES, volatility of market prices, and a lack of funds [56].

Olabi et al. [59] emphasized that the low level of public awareness is a key factor limiting the adoption of renewable energy. They suggested addressing this issue through educational programs and curricula focused on renewable energy. Osuntuyi and Lean [60] shared a similar view and confirmed that education is important for environmental sustainability because it encourages pro-environmental behavior and attitudes and supports energy-saving products and investments in green technologies. Moreover, there is empirical evidence that pro-environmental attitudes are strongly related to educational experience. The results of the study conducted by Yang et al. [61] indicated that consumers are generally willing to pay more for an increasing share of renewable energy, but it should come from a mix of different renewable energy sources. Furthermore, consumers prefer to continue working with their current energy supplier.

As noted above, the world has been suffering from a serious deterioration of the environment for years. Environmental problems have led to ecological disasters, such as extreme weather events and sea level rise. Due to this, countries are under pressure to solve environmental crises and maintain economic growth at the same time [60]. In this context, many scientists and policymakers have drawn attention to the relationship between climate change, renewable energy production, and sustainable economic growth. For example, the results of the research by Magazzino et al. [62] indicated that the use of renewable energy is a useful policy instrument to reduce CO_2 emissions without negatively affecting the GDP growth. Moreover, reducing CO_2 emissions by increasing the use of renewable energy can guarantee a high level of energy efficiency and economic growth. Jebli and Youssef [63] investigated the dynamic causal relationship between real gross domestic product (GDP) per capita, renewable energy and waste (CRW) consumption, and CO_2 emissions for five North African countries from 1971 to 2008. The results indicated that CO_2 emissions and CRW consumption have a positive and statistically significant impact on the GDP. The authors argued that countries should use more CRW because it increases their production, reduces energy dependence on fossil energy, and can reduce CO_2 emissions. Belaïd and Zrelli [64] investigated the relationship between CO_2 emissions and electricity from renewable sources and found that RES have a positive impact on environmental quality, unlike non-renewable sources. The results of the study by Alavijeh et al. [65], conducted among 14 EU countries, suggested that policymakers should create guidelines to mitigate carbon dioxide emissions by promoting innovative environmental technologies and investing in renewable energy development. A significant number of other studies also suggested that renewable energy helps in reducing environmental degradation [66,67].

Encouraging investment in renewable energy and low-emission technologies will be a key challenge in achieving the pollution reduction targets. Research in this area can contribute to the design of innovative energy policy roadmaps and accelerate the ecological transformation by promoting renewable energy and reducing greenhouse gas emissions.

2.3. Use of Artificial Neural Networks

Analytical approaches hold a significant place in examining renewable energy consumption and its environmental effects, as they facilitate the examination and interpretation of complex, multidimensional datasets. As a first step in the analysis, the data can be visualized using *t*-distributed stochastic neighbor embedding (*t*-SNE), which facilitates the understanding of their structure [68]. Among the many interesting methods used to identify non-linear patterns and relationships, the SOM is noteworthy [69]. Spatial and temporal anomalies, on the other hand, can be detected with density-based spatial clustering of applications with noise (DBSCAN) [70]. To assess the quality of the clustering results, the Calinski–Harabasz (VRC) [71] and Davies–Bouldin [72] criteria are applied. The detection of anomalies, deviations, or abnormal patterns in the dataset and the early identification of

potential problems in renewable energy monitoring systems are enabled by the one-class support vector machine (SVM) [73] and the robust random cut forest [74].

In recent years, interest has grown in applying artificial neural networks (ANNs) and other machine learning (ML) techniques for the analysis and forecasting within the realms of energy sustainability and environmental protection across EU countries. Among the publications focusing on the study of different energy consumption strategies and patterns in EU countries and assessing their impact on energy sustainability is the work of Salkuti et al. [75], who applied artificial neural networks to analyze the energy strategies of the EU countries, identifying groups of countries with similar approaches to energy diversification. In contrast, Kosowski et al. [76] examined the structure of primary energy consumption in Europe in 1990 and 2021, using cluster analysis to categorize countries based on energy consumption patterns, indicating the increasing importance of RES and the need for a diversified energy strategy. Artyukhova et al. [77] employed classification and regression trees (CART) along with clustering and agglomeration techniques to examine the relationships between renewable energy consumption and various economic, environmental, and social factors. Magazzino et al. [62] utilized artificial neural networks to reveal the influence of CO_2 emissions and fossil fuel usage on logistics indicators within the context of green supply chain management (GSCM). Authors Tutak and Brodny [12], employing a Kohonen network, evaluated the influence of renewable energy on the EU economy, highlighting its positive effects on economic growth and the reduction of greenhouse gas emissions. Interesting research results have been reported in papers dedicated to forecasting energy consumption and optimizing the use of renewable energy using advanced predictive models and machine learning techniques. For example, Negri et al. [78] proposed a model predictive control (MPC) for renewable energy communities (REC), using artificial neural networks to predict insolation, temperature, energy price, and CO_2 intensity, which optimized energy management and reduced emissions. On the other hand, Kamani and Ardehali [79] demonstrated that applying artificial neural networks in conjunction with particle swarm optimization (PSO) and extended PSO (E-PSO) algorithms can lead to substantial reductions in electricity consumption and CO_2 emissions, aligning with the objectives of the Paris Agreement. Wu et al. [80] developed multidimensional spatiotemporal graph neural networks (MST-GNN) for wind speed prediction, achieving an 8.96% accuracy advantage over other methods. Laureti et al. [81] investigated the impact of renewable energy production on a circular economy using the *k*-means algorithm and convolutional neural networks (CNNs) for forecasting, highlighting the effectiveness of linear regression and the need for less complex algorithms for better statistical results. Kayakuş et al. [82] analyzed the forecasting of carbon emissions in Turkey using artificial neural networks in relation to the Paris Agreement and the EU Green Deal, showing that emissions in 2030 could be 42% higher than the targets if appropriate action is not taken. In contrast, Brodny and Tutak [83] used Kohonen networks to analyze the structure of energy consumption in the EU industrial sector, identifying the directions and intensity of change associated with the energy transition.

Continuing with the application of artificial neural networks and machine learning models, it is essential to note the work of Han et al. [84], who developed a CO_2 emission prediction model based on residual neural networks (RESNETs), analyzing energy demands and CO_2 emissions across 24 countries. The model outperformed traditional methods, such as CNN and extreme learning machine (ELM), in terms of accuracy and efficiency in optimizing energy structures. Zhang et al. [85] applied artificial neural networks to analyze perceptions of greenhouse gas emissions on Twitter, discovering that renewable energy providers had more influence on discourse than government institutions. Jain et al. [86] focused on the role of artificial neural networks in smart cities, identifying key themes around the impact of technology on the environment and transport systems in the context of Sustainable Development Goal 11 (SDG11).

Publications focusing on the analysis and evaluation of different deep learning models used in the subject matter are interesting. For example, Ying et al. [87] reviewed the

literature on deep learning models used in renewable energy forecasting, highlighting the potential of SAE (stacked autoencoder), DBN (deep belief network), CNN (convolutional neural network), GAN (generative adversarial networks), and RNN (recurrent neural network) models in improving forecast accuracy and managing different renewable energy systems. Mogoș et al. [38] studied greenhouse gas emissions in the EU countries before and after the Green Deal, using the DM-CRISP (Data Mining—Cross-Industry Standard Process for Data Mining) methodology and cluster analysis. The authors identified the main country groups and industry sectors in terms of emissions in 2018 and 2020. Krechowicz et al. [88] analyzed the application of machine learning models in renewable energy forecasting, pointing to the popularity of ELM and ensemble methods, highlighting the key criteria, namely, energy sources, hybrid models, short-term forecasts, and number of citations.

The literature review identified several methodological gaps, the elimination of which could contribute to more diverse and comprehensive research on renewable energy and environmental degradation. There is a noticeable deficit in comparisons of the effectiveness of different clustering methods, which limits a comprehensive understanding of their advantages and disadvantages. Certain studies focus on a limited set of energy source inputs, potentially missing a comprehensive view of overall energy consumption and its environmental impacts. Many articles discuss short-term analyses, neglecting long-term projections and their impact on the energy policy. Most studies focus on data from specific countries or regions, which may limit the ability to generalize results to other areas.

3. Materials and Methods

The EU's policy on RES and environmental degradation is a central component of its sustainable development strategy. The EU aims to boost the share of RES in energy production and progressively phase out fossil fuels to reach climate neutrality by 2050. Comprehensive action plans have been established to transform Europe into the first climate-neutral continent by 2050. These plans include the European Green Deal, the Renewable Energy Directive II (RED II), and the Clean Energy for All Europeans Package. In the area of combating environmental degradation, the EU policy also focuses on nature protection, biodiversity conservation, sustainable management of natural resources, and pollution reduction, with a wide range of actions and regulations aimed at protecting natural ecosystems, ensuring sustainable resource management, and minimizing the negative impact of human activities on nature.

3.1. Data Source

The research conducted focused on evaluating changes in the use of RES and the extent of environmental degradation in the EU countries in 2015, 2019, and 2021. This timeframe encompasses the year prior to the COVID-19 pandemic as well as the year marking its conclusion. Additionally, 2015 was included in the study to observe the direction of changes in RES usage and environmental degradation levels, aiming to determine whether the pandemic slowed the progress in these areas and if the observed trends align with the EU priorities, such as the European Green Deal and other initiatives.

For the study, variables developed and published by Eurostat, as well as information from the database TheGlobalEconomy.com, were selected. Despite certain limitations, such as the absence of data on geothermal energy usage, the prepared set of indicators allowed for the assessment of changes and comparison of RES usage and environmental degradation levels across EU member states. Among the indicators related to RES, both information on the capacity of various installations and the amount of energy produced were considered. The indicators related to the degree of environmental degradation included data on pollutant emissions, waste recycling, circular material use, and forest cover.

3.2. Self-Organizing Map Algorithm

The research conducted, which employed the Self-Organizing Map (SOM) to analyze the EU's policies on RES and environmental degradation, offered a comprehensive per-

spective on the changes taking place within EU countries. The application of the SOM to group countries based on their energy efficiency and degree of environmental degradation allowed for the identification of important patterns and trends supporting the EU's efforts to achieve climate neutrality. This approach enhanced understanding of how EU policies translate into tangible progress among countries in sustainable development, supporting decision-making processes related to implementing strategies, such as the European Green Deal.

The SOM method aims to map the relationships between objects in such a way that objects with similar features in a multidimensional data space are located close to each other on a two-dimensional neuron map. The application of the SOM for grouping EU countries provided insights into the spatial relationships between nations, enabling the identification of groups of countries with similar profiles. Although multidimensional data often pose challenges in terms of visualization and interpretation, the SOM allows for the transformation of such data into a more readable form while preserving significant relationships and patterns present in the original data. The authors emphasize that the visualization on a two-dimensional neuron grid facilitated the analysis and identification of countries with similar energy and environmental trends, which is particularly important in comparative analyses of environmental policies. Studies such as those by Vesanto et al. [89], Ultsch [90], and Kohonen [91] have demonstrated the SOM to be an effective method for analyzing multidimensional environmental data and for grouping countries.

In recent years, the SOM has gained significance as a tool for analyzing the diversity of the EU countries concerning RES and environmental degradation. Numerous interesting studies in this area have been noted in the literature. Brodny and Tutak [92] used the SOM to group the EU countries based on greenhouse gas emissions and pollution related to the mining sector, which allowed for the identification of similarities and differences in the emission structure. The findings of their study offered valuable insights into the emission reduction potential of individual countries. Similarly, Mardani et al. [93] used the SOM to group G20 countries based on CO_2 emission patterns in relation to energy consumption and economic growth. Their analysis, enhanced by the Adaptive Neuro-Fuzzy Inference System (ANFIS) and artificial neural networks, enabled precise modeling of the impact of energy on CO_2 emissions, allowing for a thorough analysis of this phenomenon.

Other studies focused on assessing environmental efficiency and sustainable development. For example, in the work by Kanmani et al. [94], who used the SOM to analyze 180 countries in terms of their environmental efficiency indicators. The model created in this way allowed for tracking countries' progress in sustainable development and was more accurate than traditional methods, such as the Environmental Performance Index (EPI). Similarly, Tutak et al. [95] applied the SOM in combination with the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method to assess the sustainable energy development of EU countries. They used 13 indicators related to energy, economy, and the environment, and the results aimed to support effective energy policy in the EU and promote sustainable development.

Further research focused on the energy transition analysis and RES efficiency. Valčić and Markuz [96] used the SOM to analyze the selected European countries in terms of energy efficiency, RES quality, energy access, and other factors affecting economic development. This work highlights the importance of the SOM in analyzing complex data related to the energy transition. A similar approach was adopted by Bucur et al. [97], who analyzed the impact of sustainable energy on mitigating climate change and meteorological anomalies, utilizing 12 years of Eurostat data. The use of the SOM enabled the identification of differences and similarities in the transition of EU countries toward green energy.

The application of the SOM was also evident in the analysis of energy balance. Vlaović et al. [98] conducted a study covering 31 countries, considering 28 indicators, such as CO_2 emissions per capita and the share of wind energy. SOM identified countries that are close to achieving the energy balance as well as areas requiring improvement. From the perspective of supporting climate strategies, Brodny and Tutak [99] used the SOM to divide

EU countries into groups with similar structures of harmful substance emissions. The analysis aimed to support the European Green Deal strategy, efficiently direct funds, and plan actions for different groups of countries, contributing to the achievement of climate neutrality goals by 2050.

The referenced literature suggests that the SOM method has emerged as a vital tool for analyzing complex data related to energy efficiency, greenhouse gas emissions, and sustainable development. It facilitates the identification of patterns and distinctions between countries, supporting decision-making processes in energy and climate policy—an essential aspect of achieving sustainable development and energy transition goals within EU countries.

The SOM has been discussed in numerous literary works, including those by Kohonen [91], Kaski and Lagus [100], Vesanto and Alhoniemi [89], and Hastie, Tibshirani, and Friedman [101]. The SOM is an unsupervised machine learning technique used for dimensionality reduction and data visualization. It seeks to project multidimensional data onto a two-dimensional grid of neurons, preserving the inherent structure as closely as possible to enable easier interpretation of results without sacrificing essential information. In the SOM learning process, input data are assigned to neurons based on their similarity. Each neuron has a weight vector, which is compared to the data vector. The neuron with the smallest difference between the vectors, known as the Best Matching Unit (BMU), is selected for modification. The weights of both the BMU and its neighboring neurons are adjusted to better match the input data. This process preserves the topological structure of the data, resulting in the clustering of similar objects in neighboring neurons. Repeating these iterations increases the precision of pattern mapping in the data.

In the SOM method, the topological neighborhood function plays a crucial role by regulating the area of influence on neighboring neurons. This function enables the mapping of multidimensional data onto a two-dimensional neuron grid while preserving their spatial relationships. Neurons located close to each other on the grid have a stronger influence on the same data, which facilitates the grouping of similar objects in neighboring areas. As a result, the structure of neurons faithfully reflects the interrelationships between the data, allowing for their visualization, and the identification of clusters and hidden patterns.

The application of theSOM for object grouping is based on the use of multidimensional data; therefore, it is essential to perform normalization (or standardization) to ensure the comparability of variables expressed in different units of measurement. Normalization involves transforming the data so that the values of individual variables fall within a similar range. One of the most commonly used methods is min–max scaling, which allows the variables to be rescaled to a specific range, typically from 0 to 1. The symbolic form of normalization is as follows:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}, \quad (1)$$

where x' is the value of the normalized variable, x is the original value of the variable, x_{min} is the minimum value of the variable, and x_{max} is the maximum value of the variable.

The SOM algorithm learns patterns by adjusting the weights of neurons in several stages iteratively. In the first phase, the algorithm generates a two-dimensional grid of neurons, where each neuron is described by a weight vector with a number of elements corresponding to the dimensionality of the input data. The weights are initialized randomly, which can have a substantial impact on the algorithm's final outcome. To minimize the risk of convergence to local minima, the algorithm can be executed multiple times with varying initial conditions. Next, the algorithm randomly selects an input data point and compares it to the weight vectors of the neurons to identify the best matching unit (BMU), which best corresponds to the data. The BMU weights are then updated using the following formula:

$$w(t+1) = w(t) + \alpha(t) \cdot (x - w(t)), \quad (2)$$

where $w(t)$ represents the weights of the neuron at time t, $\alpha(t)$ is the learning rate that changes over time, and x is the input data.

During the SOM training, the weights of the neurons in the neighborhood of the BMU are modified according to the neighborhood radius $\sigma(t)$, which decreases with successive iterations. At the beginning of the process, the weights of neurons in a wide area are updated, and as the algorithm progresses, the modifications focus on neurons closer to the BMU, leading to a more precise mapping of patterns. The learning process is iterative, continuing until the changes in the neuron weights converge to nearly zero. The number of iterations is a critical parameter that influences the accuracy of the data structure mapping with its optimal selection depending on both the data complexity and the size of the neuron map. Typically, the neighborhood radius decreases exponentially with the number of iterations, which can be expressed symbolically as:

$$\sigma(t) = \sigma_0 \cdot \exp\left(-\frac{t}{\tau}\right), \tag{3}$$

where $\sigma(t)$ is the neighborhood radius at iteration t (with t representing the iteration number), σ_0 is the initial neighborhood radius, and τ is the time constant that controls the rate at which the radius decreases.

In the SOM algorithm, the distance metric plays a fundamental role in the grouping process. The Euclidean distance is the most commonly used measure, which calculates the distance between input data vectors and the weight vectors of neurons on the grid. This process can be described in several stages:

1. Each object in the SOM is represented by a feature vector, and each neuron on the grid is assigned a weight vector with a corresponding number of dimensions.
2. In each iteration of the algorithm, the Euclidean distance is calculated between the data vector and each of the neuron weight vectors. This distance is computed using the following formula:

$$d(x, w) = \sqrt{\sum_{i=1}^{n} (x_i - w_i)^2}, \tag{4}$$

   where x_i is the value of the variable for a given object, and w_i is the weight value of the neuron for the same variable. The vector x represents the features of the object, and the vector w corresponds to the weights of the neuron.
3. The neuron with weight vectors closest to the data vector is identified as the BMU.
4. With successive iterations, the neurons adjust to the data patterns, and objects with similar features are mapped to neighboring neurons, forming clusters that reflect the similarities between objects.
5. On the final SOM map, objects positioned close to one another share similar feature values, enabling the identification of groups with common characteristics, while those located farther apart display greater differences.

The results generated using the SOM are displayed on a two-dimensional map, where each neuron represents a specific dataset, aiding in the identification of groups of objects with similar characteristics. Outliers are generally found along the map's edges, highlighting their distinct properties. Notably, the variable values associated with each neuron enable an analysis of dominant features within individual clusters. One of the popular methods for visualizing results is the U-Matrix (Unified Distance Matrix), which illustrates the distances between neurons using colors, making it easier to identify cluster boundaries. Areas with small distances indicate similar objects, while large distances signal significant differences. The SOM can also be used to analyze changes over time by visualizing data from different periods. In the case of time-varying data, modified versions of the SOM or additional techniques, such as the Time-Adaptive SOM (TASOM), are typically used.

4. Results

The study of complex phenomena, which include the use of RES and the degree of environmental degradation in EU countries using multivariate analysis methods, requires a multi-stage study. The next steps of such a study are presented in Figure 1.

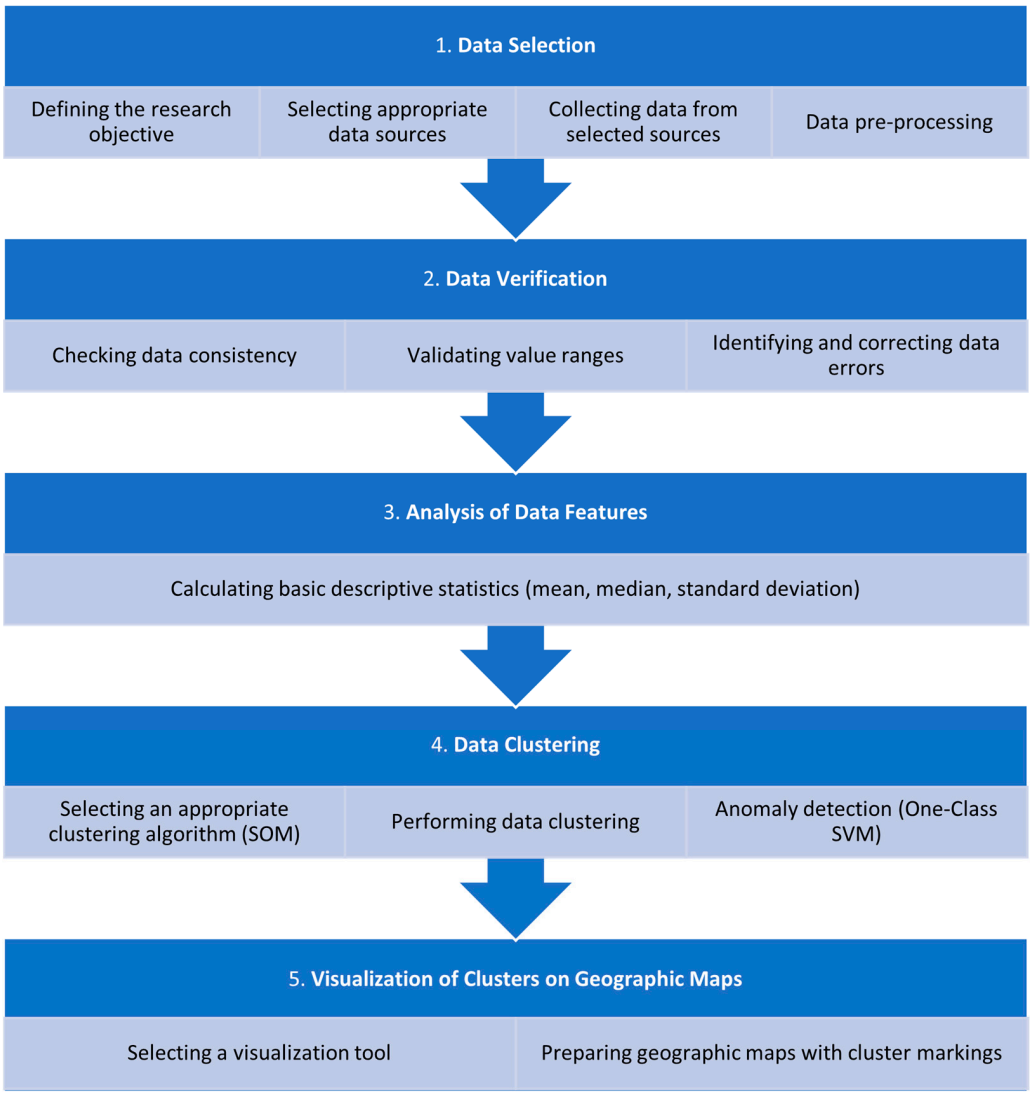


Figure 1. Stages of the study.

4.1. Data Selection and Verification

Once the set of indicators adopted for the assessment of the EU countries in terms of degradation and RES use was established and the data collected, their values were verified. This process is important and includes eliminating errors and ensuring that the results based on the data are reliable. The collected data were checked for consistency, ranges of values, and missing information. Individual data gaps were filled using statistical methods to estimate them. In the case of a large number of missing data in relation to pre-selected indicators, it was decided not to include these indicators in the study.

The grouping of the EU countries in 2015, 2019, and 2021 was carried out in terms of three aspects. The first one concerned grouping due to a set of variables consisting of indicators for the degree of environmental degradation, the next grouping included EU countries, taking into account indicators describing the use of RES, while the last grouping of countries used a set of indicators including both indicators for the degree of environmental degradation and the use of RES.

To assess the degree of environmental degradation in the EU countries, the indicators presented in Table 1 were used [102].

Table 1. Indicators characterizing the degree of environmental degradation in EU countries.

Variable	Variable Name	Unit	Characteristics
Y_1	Air emission intensity of PM2.5 from industry	Grams per euro	This indicator measures the emission intensity of fine particulate matter (PM2.5) from the manufacturing sector. Fine particulate matter has a diameter of less than 2.5 µm. Its negative effects on health are more serious than PM10, as it can be drawn further into the lungs and can be more toxic.
Y_2	Recycling rate of municipal waste	%	The indicator measures the tonnage of municipal waste recycled divided by the total amount of municipal waste. Recycling includes recycling materials, composting and anaerobic digestion, and preparing for reuse. Municipal waste consists mainly of waste generated by households.
Y_3	Raw material consumption	Tons per capita	The material footprint, also referred to as raw material consumption (RMC), represents the global demand for the extraction of materials (minerals, metal ores, biomass, and fossil energy materials) caused by the consumption of goods and services in a geographical reference area.
Y_4	Consumption footprint—single weighted score	Per inhabitant	The consumption footprint is a set of 16 indicators based on the Life Cycle Assessment (LCA) to assess the environmental impact of consumption in the EU and its member states by combining data on consumption intensity and the environmental impact of representative products. It is based on a combination of emissions to air, soil, and water, as well as resources used throughout the life cycle of around 165 representative products, belonging to 5 consumption areas (food, mobility, housing, household goods, and appliances), the consumption intensity of these products, which is calculated based on consumption statistics, and the environmental footprint (EF) impact assessment method, which translates emissions and resource use into 16 potential environmental impacts that can be aggregated into a single score.
Y_5	Circular material use rate	%	The circular material use rate (CMR) measures the share of materials recovered and returned to the economy in overall material consumption. CMU is defined as the ratio of circular material use to the overall material use. Total material consumption is measured by adding up the total national material consumption (DMC) and circular material usage. DMC is defined in economy-wide material flow accounts. The circular use of materials is approximated by the amount of waste recycled in domestic recovery facilities minus imported waste for recovery plus exported waste for recovery abroad. A higher CMU means that more secondary materials are replacing primary raw materials, thus reducing the environmental impact of primary raw material extraction.
Y_6	Net greenhouse gas emissions	Tons per capita	The index measures the total domestic emissions of greenhouse gases, including those of international aviation, the so-called "Kyoto basket".
Y_7	Average CO_2 emissions per km from new passenger cars	g CO_2 per km	The indicator is defined as the average carbon dioxide (CO_2) emissions per kilometer of new passenger cars in a given year. The reported emissions are based on type-approval and may deviate from the actual CO_2 emissions of new cars.

Table 1. *Cont.*

Variable	Variable Name	Unit	Characteristics
Y_8	Drought impact area on ecosystems	%	This indicator shows the area affected by drought in % of the total area of the country. It monitors negative anomalies in vegetation productivity in areas with a severe deficit in soil moisture during the growing season. The indicator includes only agricultural droughts, with soil moisture deficits resulting in reduced vegetation productivity due to insufficient rainfall.
Y_9	Forest area	%	It is the percentage ratio of the area of forests to the total area of a given region (country, province, district, and commune).

The variables presented in Table 2 were used to assess the use of RES in EU countries [102].

Table 2. Variables regarding RES.

Variable	Variable Name	Unit	Characteristics
X_1	Renewable power capacity	million kilowatts (MW)	The combined capacity of all installed energy generation systems using renewable sources, such as solar, wind, hydro, biomass, and geothermal. A key indicator that helps assess the potential and development of the RES sector in a given region or country.
X_2	Renewable power generation	billion kilowatt-hours (GWh)	Real energy supplied to the grid or used over a specified period of time.
X_3	Share of clean energy	%	A key indicator that shows to what extent energy from RES replaces traditional, non-renewable sources.
X_4	Share of renewables in electricity production	%	The percentage share of electricity generated from renewable sources (RES) in the total electricity production in a given country, region, or world. An indicator that allows you to assess how much electricity comes from clean and sustainable sources.
X_5	Wind electricity capacity	million kilowatts (MW)	Maximum capacity to produce electricity under ideal wind conditions. A key indicator in assessing production potential, planning investments, and understanding the impact of wind farms on the energy system.
X_6	Wind electricity generation	billion kilowatt-hours (GWh)	Wind electricity generation is the process of converting the kinetic energy of the wind into electricity using wind turbines. The key and cleanest source of renewable energy that contributes to reducing greenhouse gas emissions and promoting sustainable energy development.
X_7	Solar electricity capacity	million kilowatts (MW)	The indicator refers to the potential of photovoltaic panels to generate electricity. It refers to the ability of an installation to convert solar radiation into electricity. A key indicator for assessing the scale of solar energy use and its role in the overall energy system.
X_8	Solar electricity generation	billion kilowatt-hours (GWh)	Solar power generation involves various technologies that convert solar radiation into electricity or heat. Photovoltaics, solar collectors, and concentrated solar power systems are the main methods, each with its own unique applications and benefits.

Table 2. *Cont.*

Variable	Variable Name	Unit	Characteristics
X_9	Hydroelectricity capacity	million kilowatts (MW)	A key indicator that determines the ability of a hydroelectric power plant to generate electricity. It includes installed capacity, nominal capacity, and peak capacity, and the efficiency of the use of this capacity by the power plant. Hydroelectric power plants use the energy of flowing or falling water to produce energy, which makes them an important source of renewable energy, but also comes with the need to manage their environmental impact.
X_{10}	Hydroelectricity generation	billion kilowatt-hours (GWh)	Hydropower generation is concerned with converting the kinetic and potential energy of water into electrical energy. It includes various technologies, such as dammed power plants, run-of-river, pumped storage, tidal, and wave power plants. Each of these technologies has its own advantages and challenges, and the efficiency and environmental impact depend on the specifics of the project and location.

In order to make the variables studied comparable for the EU countries, they were converted per 100,000 population of the country.

4.2. Analysis of Data Features

Table 3 presents the values of the basic parameters of the distribution of indicators characterizing the degree of environmental degradation.

The distributions of the studied indicators were characterized by different strengths and directions of asymmetry. The strongest right-sided asymmetry occurred with respect to the Y_8 index—the drought impact area on ecosystems, the distribution of which also had the strongest variability. The highest Y_8 values were observed for Cyprus and Greece. The drought impact area on ecosystems was several times higher than the average for all EU countries. Such a high value of the indicator is due to the geographical location of these countries and the effects of climate change, such as fires. A positive phenomenon was the decrease in the average Y_8, which in 2021 was twice lower than in 2015. The weakest right-sided asymmetry was characterized by the Y_4 index—consumption footprint—single weighted score. The weakest volatility was also recorded in the case of Y_4 for each year of analysis. Due to the fact that a high consumption footprint leads to accelerated environmental degradation, countries should reduce its size by conserving resources, recycling, changing consumption patterns, and using renewable energy sources. This applies, in particular, to countries such as Ireland, Luxembourg, and Malta, where Y_4 values were significantly higher than the EU average. Among the indicators characterizing the degree of environmental degradation, there are those whose distributions had a left-hand direction. These indicators included Y_7—average CO_2 emissions per km from new passenger cars, and Y_2—recycling rate of municipal waste. An interesting situation was observed in relation to the Y_2 index, whose distribution of values in 2015 had a positive asymmetry, and in the next two years of the study, 2019 and 2021, a negative asymmetry. A positive phenomenon was the increase in the average values of the recycling rate of municipal waste in the EU countries. The highest level of Y_2 was recorded, in each year of the analysis, in Germany—almost 70%, and the lowest—in Romania and Malta—about 11%.

The only indicator with negative asymmetry, in each year studied, was Y_7—average CO_2 emissions per km from new passenger cars. An interesting situation was observed in relation to its value. In 2019, its value increased significantly compared to 2015, followed by a decrease in average CO_2 emissions per km from new passenger cars in 2021, to pre-COVID-19 pandemic levels in 2015. The situation indicates that the number of new cars has been increasing since 2015. This trend occurred until 2019, and during the COVID-19

pandemic, the number of new cars purchased decreased. Although new passenger cars are increasingly efficient in terms of CO_2 emissions per kilometer, they still contribute to environmental degradation. The highest CO_2 emissions per km from new passenger cars in 2021 were observed in the Baltic countries: Lithuania, Latvia, and Estonia. The lowest were in The Netherlands, Portugal, and Denmark. A key way to reduce the impact of CO_2 emissions from cars, including new vehicles, is to promote sustainable transport, including the development of electric cars powered by renewable energy, the expansion of public transport infrastructure, as well as the change in consumer habits, such as the use of car-sharing or bicycles.

Table 3. Basic descriptive characteristics of indicators describing environmental degradation in 2015, 2019, and 2021.

Variable	Year	Mean	Median	Min	Max	Standard Deviation	Coefficient of Variation	Skewness
Y_1	2015	0.170	0.080	0.020	0.780	0.198	116.658	2.124
	2019	0.130	0.070	0.010	0.710	0.151	116.076	2.523
	2021	0.129	0.060	0.010	0.730	0.157	122.365	2.545
Y_2	2015	35.356	32.500	10.900	66.700	14.262	41.368	0.122
	2019	39.611	38.500	9.100	66.700	14.283	36.058	−0.326
	2021	41.063	42.200	11.300	69.300	15.257	37.155	−0.317
Y_3	2015	17.706	15.577	9.269	44.334	7.340	41.454	2.067
	2019	18.930	17.227	8.589	47.685	7.881	41.630	1.814
	2021	19.056	16.711	7.721	48.016	8.402	44.089	1.597
Y_4	2015	0.930	0.940	0.610	1.390	0.211	22.646	0.285
	2019	0.969	0.970	0.640	1.330	0.186	19.191	0.012
	2021	0.939	0.950	0.660	1.320	0.158	16.801	0.075
Y_5	2015	8.226	6.700	1.700	26.600	6.026	73.256	1.362
	2019	9.100	8.400	1.400	25.600	6.134	67.405	1.002
	2021	9.241	7.300	1.400	28.500	6.838	74.000	1.204
Y_6	2015	8.463	8.000	0.300	19.900	3.896	46.036	0.791
	2019	8.341	7.900	1.200	19.600	3.714	44.528	0.936
	2021	7.737	7.100	0.500	16.700	3.241	42.016	0.560
Y_7	2015	120.933	123.700	101.200	137.200	9.599	7.938	−0.326
	2019	147.793	150.000	119.300	161.200	10.393	7.032	−0.819
	2021	121.752	123.800	88.300	145.900	16.289	13.379	−0.431
Y_8	2015	2.533	0.600	0.000	21.300	4.496	177.458	3.043
	2019	7.741	4.000	0.000	50.700	11.245	145.264	2.459
	2021	1.263	0.500	0.000	6.200	1.587	125.640	1.566
Y_9	2015	34.704	34.300	1.100	73.700	16.889	48.667	0.474
	2019	34.885	34.500	1.400	73.700	16.886	48.404	0.465
	2021	34.941	34.500	1.400	73.700	16.871	48.285	0.458

In the case of indicators characterizing the degree of environmental degradation, it was noted that the beginning of the COVID-19 pandemic contributed to slowing down or accelerating the occurrence of certain phenomena. The study found that in the case of indicators such as consumption footprint—single weighted score (Y_4), net greenhouse gas emissions (Y_6), average CO_2 emissions per km from new passenger cars (Y_7), and drought impact area on ecosystems (Y_8), which have a stimulating effect on environmental degradation, there was a significant decrease in their value. On the other hand, the values of the average indicators recycling rate of municipal waste (Y_2) and circular material use rate (Y_5) increased, thus reducing the degree of environmental degradation. Figure 2 illustrates selected indicators describing environmental degradation in 2015, 2019, and 2021.

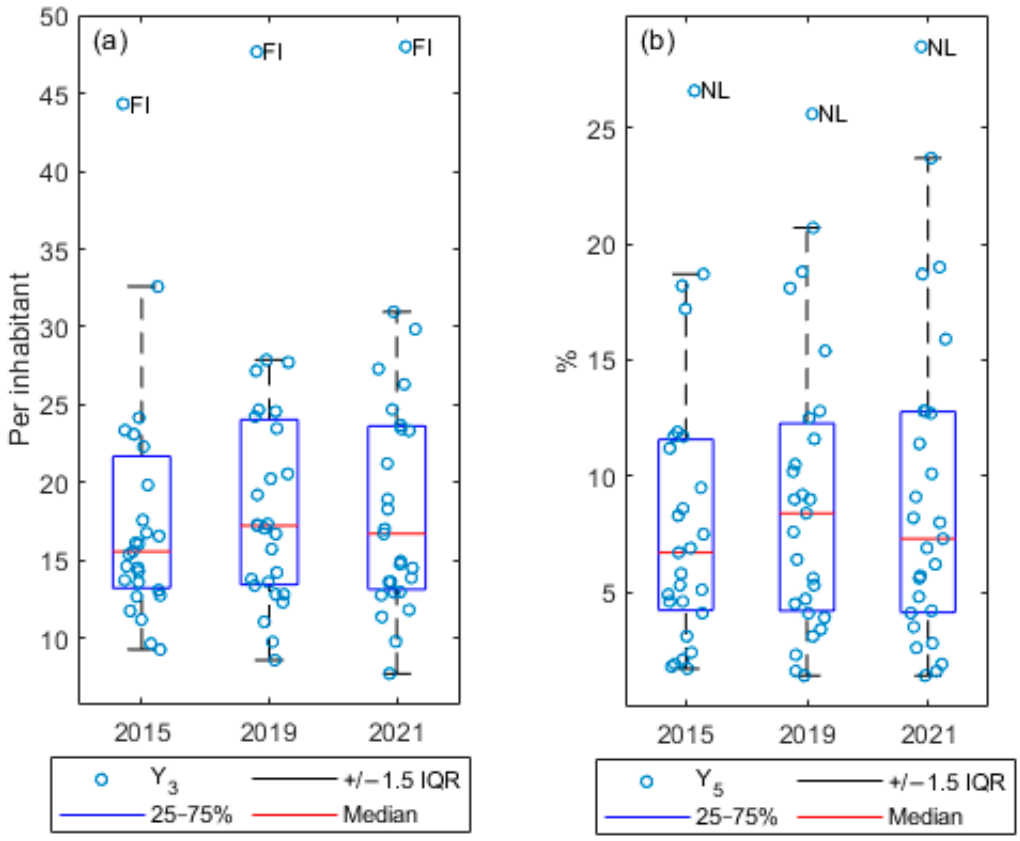


Figure 2. Selected indicators describing environmental degradation in 2015, 2019, and 2021: (**a**) raw material consumption and (**b**) circular material use rate, where FI represents Finland and NL represents The Netherlands.

The basic descriptive characteristics of the indicators describing the use of RES are presented in Table 4.

Table 4. Basic descriptive characteristics of indicators describing the use of RES in 2015, 2019, and 2021.

Variable	Year	Mean	Median	Min	Max	Standard Deviation	Coefficient of Variation	Skewness
X_1	2015	0.072	0.057	0.011	0.276	0.054	75.867	2.195
	2019	0.087	0.072	0.023	0.303	0.059	68.703	2.035
	2021	0.100	0.082	0.031	0.333	0.065	65.274	1.943
X_2	2015	0.201	0.139	0.023	1.058	0.215	106.765	2.867
	2019	0.225	0.166	0.041	0.975	0.207	91.947	2.361
	2021	0.253	0.197	0.050	1.087	0.222	87.472	2.512
X_3	2015	21.036	16.570	5.750	51.910	11.880	56.474	0.928
	2019	22.888	17.640	7.400	52.870	11.769	51.418	0.987
	2021	24.838	20.080	9.180	58.400	12.436	50.067	1.099
X_4	2015	32.450	29.390	7.690	77.030	19.547	60.238	0.726
	2019	38.204	37.330	10.010	78.550	22.033	57.673	0.521
	2021	42.281	40.220	12.160	80.490	21.859	51.700	0.344
X_5	2015	0.023	0.016	0.000	0.090	0.022	96.802	1.448
	2019	0.030	0.023	0.000	0.105	0.028	93.747	1.223
	2021	0.035	0.025	0.000	0.120	0.033	94.019	0.120

Table 4. *Cont.*

Variable	Year	Mean	Median	Min	Max	Standard Deviation	Coefficient of Variation	Skewness
X_6	2015	0.052	0.032	0.000	0.250	0.058	111.867	1.962
	2019	0.070	0.052	0.000	0.278	0.070	99.685	1.456
	2021	0.078	0.053	0.000	0.274	0.075	97.241	1.302
X_7	2015	0.012	0.010	0.000	0.048	0.012	100.223	1.124
	2019	0.018	0.016	0.000	0.059	0.014	81.321	1.129
	2021	0.026	0.022	0.001	0.082	0.020	75.332	1.259
X_8	2015	0.013	0.010	0.000	0.048	0.013	98.118	1.056
	2019	0.019	0.017	0.000	0.053	0.015	78.915	0.657
	2021	0.028	0.022	0.001	0.072	0.020	71.817	0.507
X_9	2015	0.029	0.024	0.000	0.167	0.038	131.191	2.174
	2019	0.029	0.025	0.000	0.167	0.037	129.186	2.041
	2021	0.029	0.025	0.000	0.158	0.037	129.332	2.015
X_{10}	2015	0.096	0.053	0.000	0.767	0.165	172.218	3.071
	2019	0.096	0.037	0.000	0.630	0.146	163.608	2.700
	2021	0.100	0.055	0.000	0.685	0.155	155.742	2.612

The indicators adopted to assess the use of RES were characterized by strong or very strong right-sided asymmetry. The strongest asymmetry occurred in relation to the X_{10} and X_2 indices. The occurrence of such a strong asymmetry is associated with very high values of these indicators for countries such as Sweden, France, and Italy. In these countries, a large amount of hydropower is produced, which is due to the fact that they have water resources used for its production. The weakest asymmetry was characterized by the distribution of the X_4 index—share of renewables in electricity production. A particularly low degree of asymmetry of variable distributions was noted for 2021. The indicators were also characterized by strong or very strong volatility. The strongest volatility referred to the indicator X_{10}—hydroelectricity generation per 100,000 inhabitants. The highest values of the indicator were observed for Sweden, Austria, and Finland. The lowest volatility was noted for the X_3 indicator—share of clean energy. A positive trend was the decreasing differentiation for X_3, which indicated a narrowing of the differences between countries in terms of the share of clean energy. In each of the surveyed years, the highest shares of clean energy were observed in Sweden (51.91–58.40%), Finland (43.23–47.49%), and Latvia (about 41%). The lowest shares of clean energy levels were recorded for Malta (6.00–9.18%) and The Netherlands (5.75–10.79%). Another positive phenomenon was the increase in the level of the share of clean energy in most EU countries. The largest increase was observed in the case of Estonia and Luxembourg, by just over 11 percentage points. Only with regard to Hungary and Croatia did the share of clean energy in 2021 decrease by less than 1 percentage point compared to 2015. The increase in the share of clean energy in the EU countries was reflected in the average value for this indicator, which increased by 3.8 p.p. in 2021 compared to 2015 and amounted to 24.3%. Analyzing the values of other indicators that had a stimulating effect on the volume and consumption of RES in the EU countries, it can be concluded that there was an increase in the average values of individual indicators. A significant increase was recorded for the following indicators: X_2, X_3, X_4, X_6, X_7, and X_8. A slightly smaller one was recorded for the others, among which there were indicators relating to energy from wind, water, and solar. Figure 3 illustrates selected indicators describing the use of RES in 2015, 2019, and 2021.

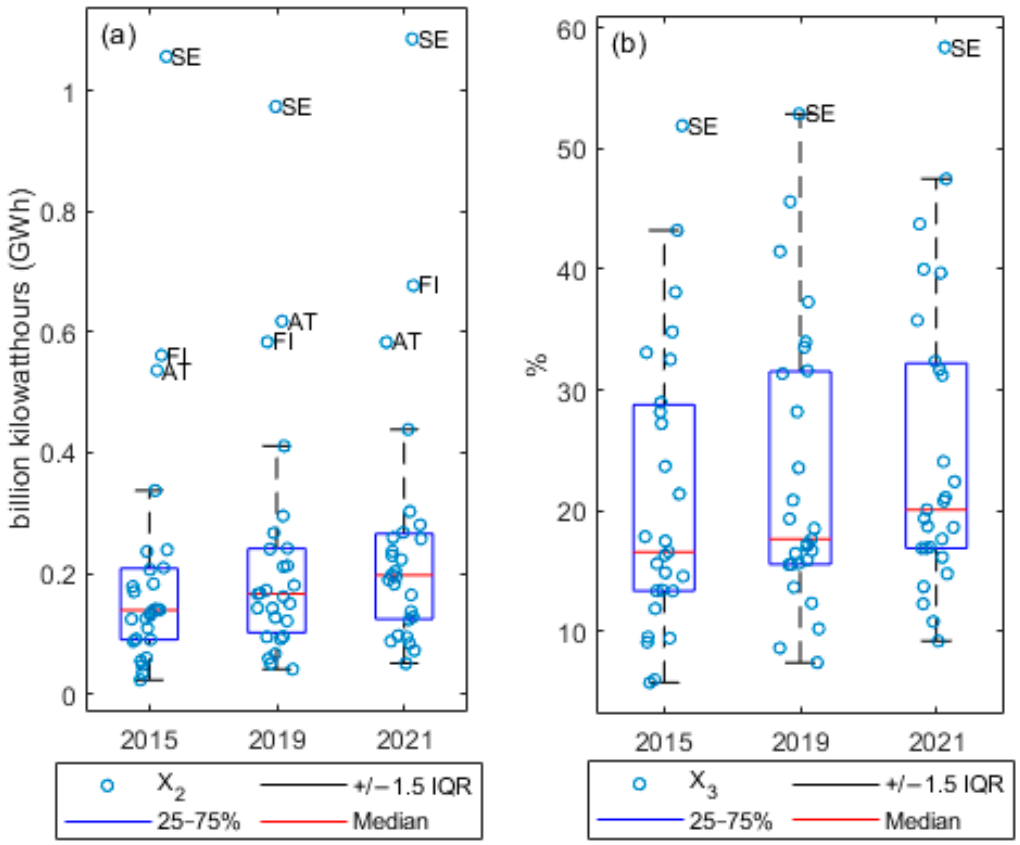


Figure 3. Selected indicators describing the use of RES in 2015, 2019, and 2021: (**a**) renewable power generation and (**b**) share of clean energy, where SE represents Sweden, FI represents Finland, and AT represents Austria.

4.3. Country Grouping

4.3.1. Introduction to Country Grouping

In order to distinguish groups of countries with a similar level of RES use and degree of environmental degradation, the method of the Self-Organizing Map (SOM) was used (Figure 4). In each year of analysis, four groups of the EU countries were obtained. As a result of the grouping carried out in 2015, 2019, and 2021, it was observed that Denmark and Sweden showed particularly high levels of the usage of renewable energy sources, which made them anomalies in RES research in Europe. Denmark, thanks to the intensive development of wind energy, and Sweden, which achieved the highest rates in terms of capacity and production of renewable energy, significantly differed from the rest of the EU countries. These exceptional results placed them outside the four main groups of countries defined in the study, justifying their treatment as exceptional cases (anomalies), both in terms of the sophistication of RES and their environmental impact. To confirm the consistency of the data and identify possible outliers, the one-class support vector machine (SVM) algorithm was used. The results of this analysis led to the exclusion of Denmark and Sweden from the RES dataset, as well as the exclusion of Sweden from the common data covering RES and environmental degradation, highlighting their unique status in the analysis. Figure 4 presents a network diagram illustrating the groups of countries obtained from the analysis using the SOM method.

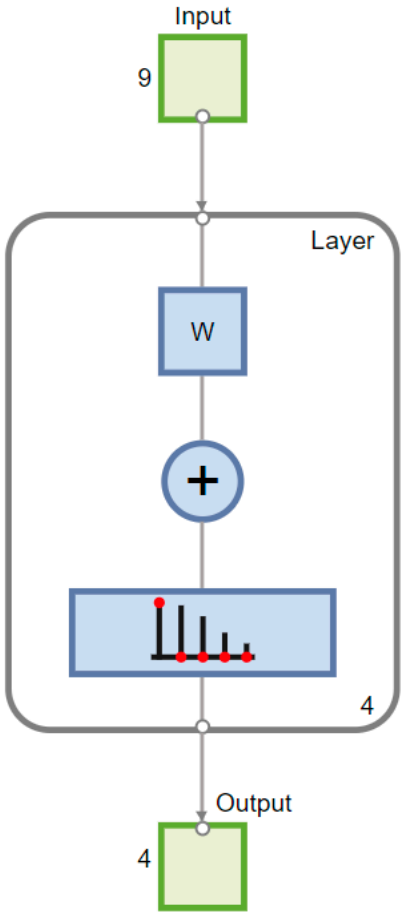


Figure 4. Network diagram, where: 9— number of inputs, 4—number of outputs, W—weights.

4.3.2. Environmental Degradation Clusters

Analyzing the results of grouping the EU countries in terms of the degree of degradation obtained for 2021, it can be seen that the largest group included as many as 10 countries: Austria, Belgium, Denmark, France, Germany, Ireland, Italy, Luxembourg, Malta, and The Netherlands. These countries had the lowest mean values of variables that were stimulants of environmental degradation: air emission intensity of PM2.5 from industry, raw material consumption, and drought impact area on ecosystems. In addition, they were characterized by the highest average values of degradation destimulants, thanks to which the degree of environmental degradation was reduced, such as the recycling rate of municipal waste and the circular material use rate. The average values of the above-mentioned stimulants and degradation destimulants were simultaneously lower and higher than the average values of these variables determined for the entire EU, which indicated a low degree of environmental degradation in the countries belonging to this group, which was also the lowest among all groups.

In 2021, the Czech Republic, Estonia, Lithuania, Poland, Slovakia, Slovenia, and Spain formed a group characterized by large average values of all degradation deteriorating rates greater than their average values for the entire EU. Most of the degradation stimulants had relatively small average values, less than the average values for the entire EU. Only two variables had unfavorable values compared to the EU averages: net greenhouse gas emissions and average CO_2 emissions from new passenger cars. Comparing the average values of the analyzed indicators, it can be concluded that in 2021, the countries in this group had a relatively low degree of degradation, meaning their moderate impact on the environment.

Only two countries belonged to the smallest group received for 2021: Finland and Sweden. They were characterized by the lowest average values of net greenhouse gas

emissions and drought impact area on ecosystems and the highest average value of forest area. In this group, the average value of air emission intensity of PM2.5 from industry was also very low. In terms of these four variables, this group had a low degree of environmental degradation, but in terms of the other five variables, the average values of which were unfavorable compared to the averages for the entire EU, the degree of degradation was high.

The next group in 2021 included eight countries: Bulgaria, Croatia, Cyprus, Greece, Hungary, Latvia, Portugal, and Romania. In this group, all environmental degradation destimulants had relatively low mean values, lower than the average values for the entire EU. This indicates the weak commitment of the countries in this group to counteract environmental degradation, especially through waste recycling and the use of materials in a closed loop. Countries in this group had the highest average air emission intensity of PM2.5 from industry and very high average CO_2 emissions from new passenger cars and drought impact areas on ecosystems. Comparing the average values of the analyzed indicators for all groups, it can be concluded that the countries in this group had the highest degree of environmental degradation in 2021.

4.3.3. Changes in Group Composition over Time—ED

Analyzing the results of grouping countries by the degree of environmental degradation in 2015, 2019, and 2021, it can be seen that the composition of the group with the lowest degree of degradation has changed little over time. In 2015, eight countries belonged to this group: Belgium, Denmark, France, Germany, Ireland, Italy, Luxembourg, and The Netherlands. In 2019, it was expanded to include Malta, and in 2021, Austria. Each year, this group had the most variables with extreme average values, confirming the effectiveness of countries' policies aimed at counteracting degradation. It should be noted, however, that in 2019, this group was in the least favorable situation in the entire EU due to the average values of consumption footprint, net greenhouse gas emissions, and forest area. In 2021, the situation in terms of these variables improved.

The other grouping results in 2015 and 2019 showed greater differences compared to 2021, both in terms of the composition of the groups and the average values of the analyzed ratios. In 2015, eleven countries were in the largest group with the highest degree of degradation: Bulgaria, Croatia, the Czech Republic, Greece, Hungary, Latvia, Lithuania, Poland, Portugal, Romania, and Slovakia. In 2019, the Czech Republic and Lithuania permanently separated from this group, and in 2021, Poland and Slovakia did. Cyprus joined it in 2019. Changes in the composition of this group were related to the change in the degree of degradation in the countries belonging to it—in 2019, it was relatively low, and in 2021 it was again the highest.

In 2015, Cyprus, Malta, and Spain were in the group with a relatively high degree of environmental degradation. In 2019, Malta was replaced by the Czech Republic, and at that time, this group was characterized by the highest degree of degradation. In 2021, Cyprus left this group, and its place was taken by Estonia, Lithuania, Poland, Slovakia, and Slovenia, alongside the Czech Republic and Spain. The degree of environmental degradation in this group decreased significantly at that time.

In 2015, the group with a relatively low degree of environmental degradation included Austria, Estonia, Finland, Slovenia, and Sweden. In 2019, Lithuania joined the group, while in 2021 most of the countries separated and only Finland and Sweden remained. In 2019 and 2021, the degree of degradation in this group increased compared to other EU countries.

Comparing the composition of individual groups in all years, it can be seen that there were countries that both advanced to groups with a lower degree of degradation and fell to groups with a higher degree of degradation. In 2019, the promotion concerned Malta, Poland, and Slovakia, whereas in 2021, Austria, the Czech Republic, Estonia, Lithuania, Slovenia, and Spain were included. Countries that were in groups with a higher degree of degradation in 2021 were Bulgaria, Croatia, Greece, Hungary, Latvia, Portugal, and Romania.

4.3.4. Renewable Energy Source Clusters

Through the grouping of the EU countries based on RES usage, distinct groups were identified, each characterized by a particular level of RES adoption and commitment to the energy transition. In 2021, one group included Austria, Finland, Latvia, Portugal, and Croatia, which stood out with the highest values of indicators related to RES. These countries recorded exceptionally high shares of clean energy and of renewables in electricity production, significantly higher than the EU average. They were also leaders in wind electricity capacity and wind energy generation, underlining their commitment to the development of this technology. On the other hand, the solar energy (solar electricity capacity and solar electricity generation) performance was below average, while hydropower was a key part of their energy mix.

Estonia, Lithuania, Romania, Slovenia, and Luxembourg, grouped in a different category, had average results, but their shares of clean energy and of renewables in electricity production values were above the EU average, although they were lower than those of the leaders. These countries have made significant progress compared to 2015, especially in solar and wind electricity generation, which indicates greater investment in these areas. However, hydroelectricity generation indicators remained low, indicating limited use of this energy source.

Germany, Spain, Greece, Italy, Belgium, and The Netherlands were in the moderate group. Their averages for shares of renewables in electricity production were lower than the EU average, although they made significant progress in wind and solar energy (wind electricity capacity, wind electricity generation, solar electricity capacity, and solar electricity generation). Compared to 2019, their performance in these areas improved, but it remained below the level of the leaders. Despite the increase in solar capacity and production, their performance was still moderate compared to the EU.

The countries with the lowest scores, such as Poland, Bulgaria, Hungary, and the Czech Republic, were included in one group. The average values of indicators, such as the share of renewables in electricity production and the share of clean energy, remained well below the EU average. Despite some progress in solar and wind energy, their development between 2015 and 2021 was slow, and the results were low compared to other groups.

4.3.5. Changes in Group Composition over Time—RES

In 2019, Belgium, The Netherlands, and Luxembourg improved their indicators, especially in terms of solar capacity and production, which allowed them to move up the ranks thanks to greater investments in renewable energy infrastructure. Austria, Finland, and Portugal, on the other hand, maintained stable, high rates, which confirmed their progress in the development of renewable energy sources.

In 2015, Austria, Finland, and Portugal were already leaders in renewable energy sources, with values well above the EU average, especially in the area of shares of clean energy and of renewables in electricity production. Although their ratios were lower than in subsequent years, this testified to their continuous, stable development in the RES area. Poland, Bulgaria, and Hungary had the lowest scores and recorded only minor changes in 2019 and 2021, indicating a limited commitment to the development of renewables.

4.3.6. ED and RES Clusters

By grouping the EU countries in terms of the use of RES and the degree of environmental degradation, four groups of countries were also obtained in each of the surveyed years. The group of six countries to which, in 2021, Belgium, Germany, Spain, France, Italy, and The Netherlands were included, was characterized by average values of variables that indicated a high degree of RES use and a low degree of environmental degradation. The average values of such indicators as solar electricity capacity and solar electricity generation significantly exceeded the average for all EU countries and were the highest compared to other groups of countries. In addition, the average renewable power capacity and the average renewable power generation in the study group remained at a high level. The

average values of many indicators relating to the degree of environmental degradation, such as the recycling rate of municipal waste or raw material consumption and circular material use rate, were characterized by favorable values, thanks to which the degree of environmental degradation in this group of countries was reduced. The drawback of this group of countries was the low percentage share of renewable energy in total energy consumption. However, according to the research, the policy of countries in this group is aimed at increasing the use of renewable energy sources, thanks to which their share in total energy consumption will also increase.

Other EU countries that are in one group include Bulgaria, Cyprus, the Czech Republic, Greece, Hungary, Malta, Poland, Romania, and Slovakia. In the case of this group of countries, many average values of indicators were recorded at a level indicating low use of RES and a high degree of environmental degradation. This situation is indicated by the average values of many indicators, including renewable power capacity, renewable power generation, share of renewables in electricity production, wind electricity capacity, and wind electricity generation, achieving the lowest averages among all the surveyed groups of countries. In addition, seven out of nine indicators relating to the degree of environmental degradation recorded the lowest averages compared to the other groups. The exceptions were the consumption footprint and net greenhouse gas emissions, for which the desired average values were recorded.

A large group consisted of the following countries: Austria, Estonia, Finland, Croatia, Lithuania, Luxembourg, Latvia, Portugal, and Slovenia. Most of the indicators relating to both the use of RES and the degree of environmental degradation were close to the average for all EU countries.

4.3.7. Changes in Group Composition over Time—ED and RES

An interesting situation has been observed for two EU countries: Denmark and Ireland. In 2015, these countries formed a group together with countries such as Belgium, Germany, Spain, France, Italy, Luxembourg, and The Netherlands. In the next two years of the survey, 2019 and 2021, the indicated countries formed a two-element group, and the remaining countries joined other groups. Denmark and Ireland formed a cluster characterized by the occurrence of average values of variables confirming high use of RES and a low degree of environmental degradation, reaching the highest average value of the indicators renewable power capacity and renewable power generation, by focusing on wind energy. The production and use of energy from the other two renewable sources, i.e., the sun and water, was at a low level. The average values of the indicators air emission intensity of PM2.5 from industry, CO_2 emissions per km from new passenger cars, and drought impact area on ecosystems were clearly lower than the average for all countries and indicated a lower degree of environmental degradation. On the other hand, consumption footprint—single weighted score, net greenhouse gas emissions, and forest area achieved average values, indicating a high impact on environmental degradation.

4.4. Visualization of Grouping Results

The results of grouping the EU countries in 2015, 2019, and 2021 due to indicators on the use of RES and the degree of environmental degradation are presented in Figure 5.

In Figure 5, the yellow color indicates countries characterized by lower use of RES and a higher degree of environmental degradation, while the darker green color represents countries with higher use of RES and a lower degree of environmental degradation.

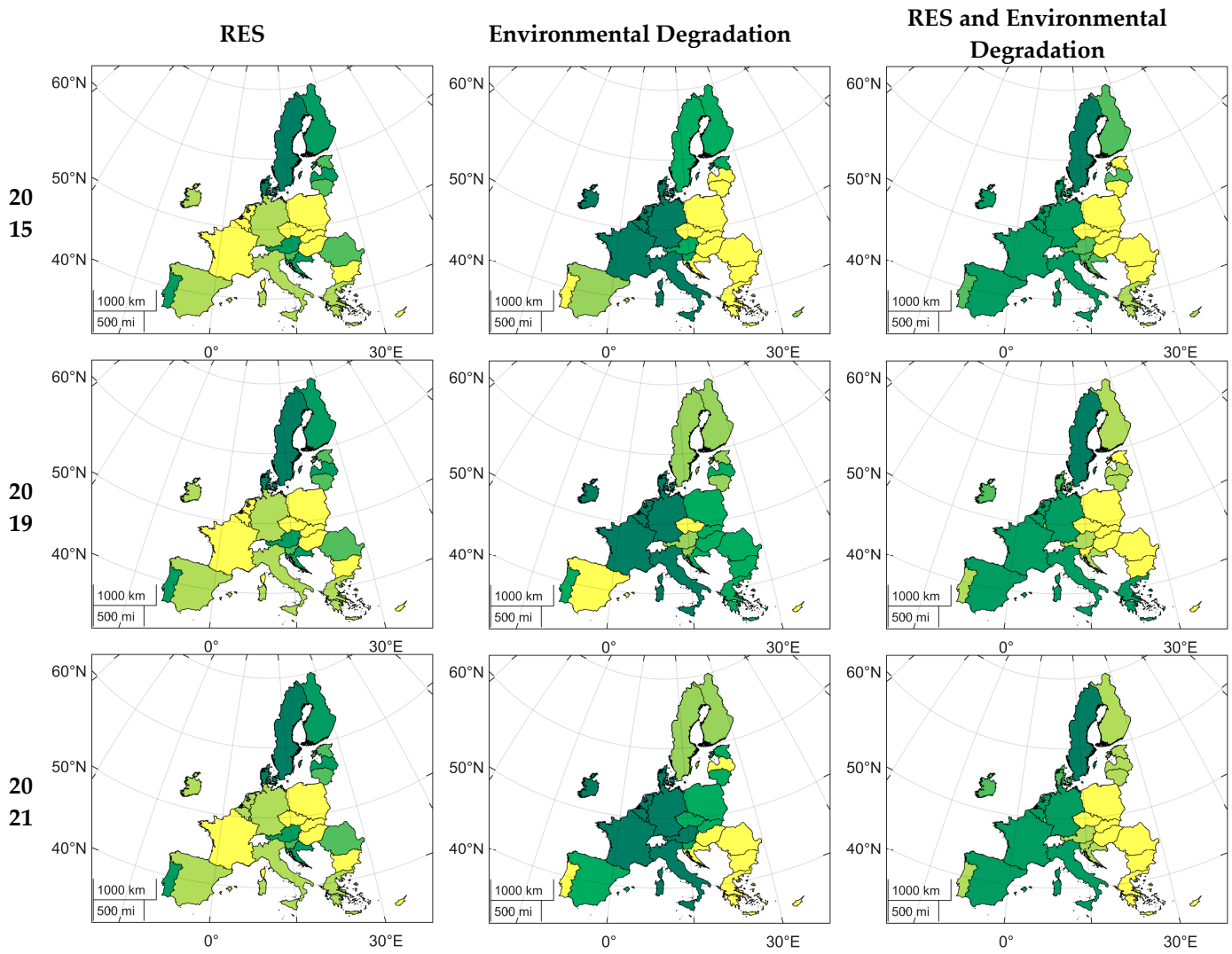


Figure 5. Results of grouping EU countries in 2015, 2019, and 2021 due to indicators on the use of RES and the degree of environmental degradation.

5. Discussion

Protecting the environment and promoting renewable energy sources are essential components of the EU policy, significantly contributing to minimizing the adverse effects of human activities in the natural world. This analysis focused on assessing the degree of environmental degradation in the EU countries and their commitment to increasing the use of RES over the years 2015, 2019, and 2021. The EU is taking intensive actions to reduce environmental degradation; however, individual member states are implementing these actions to varying degrees. Research on environmental degradation concentrates on selected aspects, primarily related to air pollution caused by gases and particulates. Dace and Blumberga [103] observed that despite the overall reduction in greenhouse gas emissions in the EU-28 (pre-Brexit members) since 2005, greenhouse gas emissions from agriculture have increased in most EU member states. Brodny and Tutak [99] examined the reduction in greenhouse gas emissions into the atmosphere in the EU-28 from 2007 to 2017. Denmark and Finland were leaders in this reduction, while Poland was in the worst situation due to its energy policy primarily based on hard coal and lignite. Fugiel et al. [104] studied the impact of air pollution emissions from the mining and extraction sector on the environment in 12 European countries. Through the use of Life Cycle Assessment techniques, the authors showed that in 2012, the highest environmental damage rates were experienced in the United Kingdom, Poland, Norway, and Germany. Mushafik and

Prusak [105], who analyzed resource productivity and environmental degradation in the EU-27 (post-Brexit members) from 2000 to 2020, found that Luxembourg and Ireland had the highest levels of environmental degradation, while Sweden had the lowest.

Our analyses addressed the issue of environmental degradation in a broader context, encompassing not only greenhouse gas emissions, but also indicators related to waste recycling, consumption footprint, and material use within the framework of a circular economy. This approach makes the assessment of environmental degradation in the EU countries more comprehensive, extending beyond emission analysis alone. The results of our research showed that countries such as Bulgaria, Cyprus, Hungary, the Czech Republic, Romania, Latvia, Slovakia, and Poland consistently belonged to the group with the highest levels of degradation in all years studied. In contrast, Belgium, Denmark, France, Ireland, Italy, The Netherlands, Finland, and Sweden represented the group of countries with the lowest levels of environmental degradation. Brodny and Tutak [99] demonstrated that Denmark and Ireland exhibited the highest levels of gas and particulate emissions per capita, but in our analysis, which included multiple environmental indicators, these countries were classified in the group with lower levels of degradation.

In December 2019, the European Commission unveiled the European Green Deal, an ambitious plan designed to make the EU climate-neutral by 2050. However, almost simultaneously, the outbreak of the COVID-19 pandemic significantly impacted the global economies and the state of the environment, causing temporary shifts in the dynamics of emissions and pro-environmental actions. Pandemic-related lockdowns contributed to a temporary reduction in greenhouse gas emissions, as confirmed by data from the European Space Agency [106,107]. Nevertheless, the post-pandemic economic recovery led to a short-term increase in emissions, especially in the developing countries [16]. Our research revealed that in countries such as Bulgaria, Croatia, Greece, Hungary, Latvia, Portugal, and Romania, the level of environmental degradation decreased in 2019, but grew again in 2021, reaching the highest values across the entire EU.

Research on RES in the EU countries indicates significant variation in the level of development of these technologies. Northern European countries, such as Sweden, Denmark, and Finland, stand out with a high share of RES in their national energy mixes [108,109]. Studies on renewable energy have been conducted by many experts, covering virtually all countries worldwide, including the EU member states. The results show substantial disparities in the development of RES among the EU members. The Northern European countries are characterized by a higher share of renewable energy in their energy mix [108]. The research by Miłek et al. [109], conducted in 2012 and 2020, revealed that the leaders in RES development were Sweden, Denmark, Finland, and Estonia, while Malta and Poland were part of the group of countries with the lowest levels of RES development.

Our research also confirmed that the Scandinavian countries led in the use of RES, while countries such as Bulgaria, the Czech Republic, Hungary, Poland, and Slovakia achieved lower results and belonged to the group with the lowest levels of RES utilization. Island nations, such as Malta and Cyprus, despite having significant potential, also exhibited low levels of RES implementation. Similar conclusions were drawn by Megyesiova et al. [110], highlighting Sweden and Finland as leading countries that, despite high energy consumption, rely more on RES, contributing to progress toward affordable and clean energy. This was further confirmed by the analyses of Oesterreich and Wawrzyniak [111], who, examining renewable energy production and consumption in 2020, identified three Northern European countries (Sweden, Denmark, and Finland) and two Baltic countries (Latvia and Lithuania) as leaders in this field.

Ligus and Peternek [112] demonstrated that in the years 2017–2018, countries such as Denmark, Luxembourg, Austria, and Sweden were classified as leaders in sustainable energy development. The results of this research clearly indicated that Sweden ranked first in the monitored scope. On the other hand, the countries with the worst performance in RES implementation included Estonia, Malta, Slovakia, Poland, Greece, Cyprus, and Bulgaria. Meanwhile, Siksnelyte-Butkiene et al. [113] pointed out that Greece, Croatia, Italy, Portugal,

and Romania have great potential for reducing greenhouse gas emissions, developing RES, and improving energy efficiency. The group of countries facing greater challenges in achieving climate and energy goals included France, Belgium, Ireland, and Poland. The key challenges arise from insufficient emission reductions and a strong dependence on fossil fuels, such as coal in Poland, oil and natural gas in Belgium, and nuclear energy, oil, and gas in France.

In recent years, a few interesting studies have been conducted using the SOM method to group the EU countries based on energy and environmental indicators. Brodny and Tutak [92] identified four clusters, with Denmark, Estonia, Finland, and Sweden in the group with the lowest emissions, and Germany, France, Poland, and the United Kingdom in the cluster with the highest emissions. Meanwhile, Bucur et al. [97] identified six clusters, with France, Germany, Sweden, and the United Kingdom in the group with the highest level of advancement in the green energy transition, while Bulgaria, Croatia, Estonia (in later years), and Poland (in earlier years) were included in the group with the lowest level of this transition. Nilashi et al. [114] considered both environmental and social sustainability indicators, which allowed them to distinguish eight clusters. Switzerland, Sweden, Finland, and Norway were placed in the group with the highest level of development, while Sudan, Pakistan, and Mauritania were in the group with the lowest indicators. Research by Vlaović et al. [98] led to the identification of eight clusters, with Denmark and Sweden in the group of countries with the highest level of energy transition and Kazakhstan and Ukraine in the cluster with the lowest level. A review of these studies and a comparison with the results presented in this article indicated similar trends in differentiating the EU countries in terms of RES utilization and the level of environmental degradation. The Northern European countries recorded the highest levels of sustainable energy development, while the Central and Eastern European countries performed worse, mainly due to their greater reliance on fossil fuels and slower adoption of green technologies.

6. Conclusions

By 2021, the EU countries had made progress toward mitigating climate change and implementing renewable energy. In 2019, greenhouse gas emissions were 32% lower than in 1990 and had already exceeded the 2020 target of reducing them by 20%. In 2021, the emission reduction amounted to over 28%. The target of a 20% share of energy from renewable sources was also achieved, and in 2021 this share amounted to almost 22%.

Analyzing the degree of environmental degradation and the use of RES in the years 2015, 2019, and 2021, we observed that the EU countries where these phenomena were at less favorable levels were adjusting their environmental protection measures to meet the requirements set out in the latest WHO recommendations and the European Green Deal [25]. In the EU member states, there was an improvement in indicators, such as the increased share of RES in energy production and consumption, and the promotion of the circular economy through initiatives such as recycling and waste minimization. However, it should be noted that aligning national policies with the 2050 Agenda is a complex process and varies depending on the specific circumstances of each country, particularly its natural resources, economic structure, and level of technological advancement. It is important to emphasize that the achievement of the EU's climate goals, such as those outlined in the European Green Deal and the 2030 Agenda, will be crucial for the further development of RES and the reduction of environmental degradation. In the long-term perspective, adapting national policies to the EU's climate neutrality strategy will be especially important, as it may lead to greater consistency of actions. Grouping EU countries for the years 2015, 2019, and 2021 provided valuable insights regarding the following:

- The degree of environmental degradation. The countries with the lowest levels of degradation in each of the analyzed years were Belgium, Denmark, France, Germany, Ireland, Italy, Luxembourg, and The Netherlands. In 2019, Malta joined this group, and in 2021, Austria. The group of countries with the highest levels of degradation varied from year to year. In 2015, it included Bulgaria, Croatia, the Czech Republic,

Greece, Hungary, Latvia, Lithuania, Poland, Portugal, Romania, and Slovakia, but the situation in these countries improved by 2019. However, after the COVID-19 pandemic, the degree of degradation increased again, with countries such as Bulgaria, Croatia, Greece, Hungary, Latvia, Portugal, and Romania among those with the highest levels of degradation.

- Differences in the degree of RES implementation among the EU countries. In 2015, the leaders in RES integration were Austria, Finland, Latvia, Portugal, and Croatia, thanks to strong investments in wind, solar, and hydropower. Their high level of commitment continued in subsequent years. The year 2019 saw improvements in RES indicators for Belgium, The Netherlands, and Luxembourg, which significantly increased their investments in solar and wind energy. By 2021, Belgium, The Netherlands, and Luxembourg continued this growth trajectory.

Poland, during the analyzed period, recorded only moderate progress in the development of RES. Although both the capacity and production of renewable energy increased, the rate of growth was much lower compared to many other EU countries. Technological advancements, including energy storage and innovative solutions in wind and solar energy, open new opportunities for countries with lower RES shares. In particular, improvements in energy storage efficiency and the development of smart energy grids can accelerate the energy transition process in countries such as Poland, Hungary, and Bulgaria, enabling more efficient use of RES.

The greatest progress in RES development between 2015 and 2021 was recorded by Denmark and Sweden. Both countries successfully increased their energy capacity in the renewable sector, particularly in wind and solar power, and significantly contributed to the growth of RES in electricity production. Their advanced approach to the energy transition has made them global leaders in RES implementation rankings, further emphasizing their role in global initiatives for sustainable development.

RES indicators in many EU countries significantly increased during the analyzed period, reflecting a growing commitment to the energy transition. The capacity of renewable energy and its share in the final electricity consumption were higher in 2021 compared to 2015. However, countries such as Bulgaria and Hungary showed a much slower growth rate, and their renewable energy indicators remained at a low level. Greater investments in RES can bring numerous economic and social benefits, including improved economic competitiveness and the development of new technologies. Countries that make substantial investments in the renewable energy sector can anticipate job growth in the green technology industry and enhanced quality of life for their citizens, thanks to lower pollution levels and increased access to clean energy. The energy transition also supports local economies, creating conditions for more sustainable regional development.

In summary, our research show that the Northern European countries maintain their leading position in the energy transition, while the Central and Eastern European countries face greater challenges in achieving climate goals. Despite improvements in RES indicators in many EU countries, significant differences in the level of commitment to RES development and environmental degradation reduction remain. Accelerating this process, especially in countries with lower RES shares, will be crucial for achieving the EU's climate goals. A key component of the energy transition is also increasing public acceptance of RES, which can be achieved through educational campaigns and programs that raise awareness of the benefits of clean energy. Achieving the EU's climate goals requires intensified cooperation among member states and building strong partnerships with countries outside the European Union, which will help accelerate the global energy transition.

7. Limitations and Future Research

Research on the use of RES and issues related to environmental degradation faces various limitations that can affect its accuracy and comprehensiveness. From our perspective, the lack of long-term data for different countries is a major challenge. Additionally, some information, such as the soil sealing index, is collected only every few years. There are also

gaps in data regarding river and groundwater pollution. Other researchers [115,116] also highlighted challenges associated with data availability and the use of specific methods. Despite these limitations, the proposed set of indicators allowed for a broad assessment of changes in RES utilization and the degree of environmental degradation, as well as the identification of the EU member states with similar levels of RES use and environmental degradation.

The scope of potential research on the use of RES and the assessment of environmental degradation is very broad. In future studies, we intend to apply other methods, including the multicriteria decision-making (MCDM). An interesting research direction is the evaluation and comparison of these phenomena in non-EU countries.

Our future research on environmental degradation and the use of RES will look at a longer timeframe to see the impact and effects of the COVID-19 pandemic and the conflict in Ukraine.

This study fills a gap in environmental protection research by using a broad set of indicators and the SOM method for clustering countries. This analysis provided valuable insights for policymakers at various levels, supporting effective environmental protection measures. Necessary actions include raising public awareness and education. It is also important to highlight the benefits of reducing environmental degradation and increasing the use of electricity generated from renewable sources.

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