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MODELING NATIONAL DECARBONIZATION CAPABILITIES USING KOHONEN MAPS

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This study sought to develop a method to cluster countries based on their decarbonization capabilities and to determine how these nations' reduction of carbon dioxide (CO_2) emissions has evolved over time. CO_2 emissions clusters were identified using 11 indicators that measure both direct and indirect CO_2 emissions, differentiating countries by their economic and population growth, energy consumption, and CO_2 emission level. The panel data included 39 countries over the 10-year period of 2012–2021. The clustering was based on such type of neural networks as Kohonen self-organizing maps. This type of model facilitated grouping countries by similar decarbonization capabilities and economic development. The findings reveal that Norway and Sweden are the leaders in creating climate-resilient economies among the 39 countries analyzed. The analysis carried out can help other countries establish benchmarks for improving their own internal decarbonization activities based on leader nations' strategies and borrowing their best practices for more efficient results. This study thus contributes to the literature regarding decarbonization activities by offering a multi-country dynamic clustering method using Kohonen maps.

Keywords: *carbon dioxide (CO_2), emission target, decarbonization, clustering, self-organizing map, neural network*

JEL Classification: C45, C53, Q53, Q56

Introduction

Countries that adopted the Paris Agreement in 2015 have set as their main priorities climate change policies and decarbonization activities that necessarily involve all domestic markets' participants. Multiple countries around the world are, therefore, accelerating the transition toward decarbonization and sustainable growth.

In 2021, economic recovery (i.e., based on purchasing power parity) increased by 5.9% for the G20, which represents around 80% of global energy consumption. This growth included a 5% rebound effect on energy consumption and 5.9% carbon dioxide (CO_2) emissions from energy combustion [1]. Thus, achieving climate neutrality will require stronger international cooperation. Domestic firms from the industry and service sectors need to move toward operating more fully in sustainable value chains at the local, national, European, and international level to increase these companies' resilience and competitiveness and to achieve decarbonization targets [2]. However, this transition could become more challenging due to energy prices and the potential risks of adjusting to regulations and market demands.

In this context, researchers must examine countries' basic capacity for decarbonizing their economy, including tracking their progress using effective management and mathematical tools and measurement instruments. Monitoring mechanisms need to be developed that can identify current and future levels of CO_2 emission reduction and explore potential opportunities for expanding decarbonization potential. Although these tools have become increasingly important, they have not been adequately addressed by the existing literature.

Previous studies [3-7] have highlighted that decreasing CO_2 emissions is the primary mitigating factor for climate change. Electricity consumption can be viewed as a major indicator of each nation's development [8], yet economic growth and increased human well-being worldwide has put pressure on expendable resources and exacerbated climate change [9]. Environmental damage has also increased due to intensified energy use, urbanization, and trade [10-13].

A few researchers have applied econometric approaches to analyzing the relationship between agricultural production [14, 15], energy consumption [16-19], international trade [20, 21], and environmental pollution. Some recent studies have also emphasized the advantages of deep learning and utilized data mining techniques to achieve natural data partitioning. The latter methods include clustering, which can deal with huge amounts of data based on unsupervised machine learning. Cluster analysis is an important tool for exploratory data processing focused on summarizing information's main characteristics [22-23]. Clustering has been successfully used in varied areas, such as finance [24-26], energy use [27, 28], and CO_2 emission levels [29].

Gong et al. [27] applied a clustering method to detect provinces with cleaner energy production in China. The selected technique also facilitated the identification of provinces' efforts to introduce cleaner energy production. Csereklyei et al. [28], in turn, used model-based clustering to examine the energy profiles and paths of states participating in Australia's National Electricity Market between 2011 and 2019, thereby defining 25 distinct electricity generation clusters.

In addition, Inekwe et al. [29] identified clusters based on 72 countries' CO_2 emissions. They have used three key determinants affecting CO_2 emissions (non-renewables, population, and real GDP) and established that in most cases, a 2-cluster solution appears to be optimal. Input variables for clustering have included non-renewable (i.e., total coal, gas, and oil use) and renewable energy consumption (i.e., total hydro, wind, solar, geothermal, marine, waste, solid waste, and liquid and gaseous biofuel-derived energy).

Previous studies have been subject to significant limitations. The latter have comprised targeting a single country (e.g., China [27] and Australia [28]), having a limited focus [27, 28], or neglected time factors (i.e., dynamic impacts) [29], including variable consumption of renewable and non-renewable energy. Prior research has thus neglected to determine CO_2 emission levels for groups of countries using a dynamic approach and to assess each nation's CO_2 emissions systematically over time.

To address these gaps, the current study sought to develop a classification of countries based on their target CO_2 emission levels for 2012–2021. Two research questions were addressed:

1. What are the main country clusters based on national target CO_2 emission levels?
2. How has each country's classification changed over time, with Ukraine serving as an example?

The following tasks were undertaken to achieve this study's main goals:

1. Define and analyze the database for each nation to identify the indicators that have had an impact on CO_2 emission levels over the 10-year period.
2. Validate the list of indicators that affect CO_2 emissions for the countries analyzed.
3. Conduct cluster segmentation and examine examples of national CO_2 emission levels.
4. Analyze each cluster's traits by determining which clusters contain ecologically friendly countries and examining how Ukraine's position has changed over the analyzed period.

The next section presents the methodology (i.e., secondary data analysis and clustering method). The results section is organized around the findings for specific countries. The final section provides the main conclusions organized by research question.

Methodology

Research design

This study started by collecting secondary data from open sources providing information on factors that affect CO_2 emission levels. Different databases were compared, including the World Bank's World Development Indicators [30], United Nations Statistics Division [31], United Nations Framework Convention on Climate Change [32], International Renewable Energy Agency [33], and Eurostat [34], as well as Enerdata's [35] interactive data tool. Given the panel data available, the present research opted to rely on two sources. The first was Enerdata's World Energy & Climate Statistics – Yearbook 2022 online application [35] for energy and CO_2 emission data, which was used to cluster countries according to their target CO_2

emission levels. The second source was the World Bank's World Development Indicators database [30], which supported the current study's analysis of economic and demographic data.

Each country's target CO_2 emission level was determined by gathering data on characteristics (i.e., indicators) that affect emissions in different countries. The literature review highlighted three sets of indicators that have been found to have a strong influence on each country's identification of a CO_2 emission target. The first set includes economic and population growth factors (e.g., real GDP per capita growth and urban population). Urbanization is a key variable that stimulates economic development through varied social and structural reforms. This study focused on dynamic change factors, so real GDP per capita growth was also selected.

The second set of indicators encompasses primary energy consumption products and energy transformation. These measures include energy intensity per unit of GDP, electricity consumption, electrification, renewables' share of electricity production, wind and solar power's share of electricity production, and coal, lignite, oil product, and natural gas consumption. Oil product consumption has a stronger direct impact on countries' internally generated CO_2 emissions than oil production does.

This research concentrated on decarbonization at the national level, so external consumption and production were excluded from the panel data. Total primary energy consumption was also removed to avoid double counting because energy product consumption is part of total energy consumption. In addition, electricity production corresponds to gross production and includes both public production (i.e., private and public electricity utilities' production) and industrial production (i.e., for the utilities' own uses) [35]. Electrification and electricity consumption pollute but to a different degree, so both determining factors had to be included.

The third set of indicators is related to greenhouse gas (GHG) emissions. These measures provide information about emissions from energy combustion (i.e., >80% of CO_2 emissions) and, in particular, the average CO_2 emission factor.

The sample under analysis was limited to 39 countries as the selected databases provided full, comprehensive, and updated information (i.e., key energy and climate statistics) about these nations, with minimal data gaps. As mentioned previously, the data on indicators from the first subset were obtained from the World Bank's World Development Indicators database [30]. Data for the last two indicator sets were collected from Enerdata's World Energy & Climate Statistics – Yearbook 2022 interactive online application [35].

Data analysis

A comprehensive table of data for the 39 countries selected for analysis contains 11 indicators' normalized values ranging from 0 to 1 (i.e., 0 = indicator's smallest value; 1 = largest value), as shown in Table 1. The proposed list of indicators can be reduced during data analysis if a specific measure fails to have a significant impact on the clustering process (i.e., indicator values more or less evenly distributed across different clusters).

Table 1

PORTION OF DATABASE ON INDICATORS OF CARBON DIOXIDE (CO_2) EMISSION LEVELS

Indicators / Countries	Energy intensity per unit of GDP	Oil product domestic consumption	Natural gas domestic consumption	Electricity consumption	Renewables share of electricity	Wind/solar power share of electricity	Average CO_2 emission factor	GDP per capita growth (annual %)	Urban population (% of total population)	Coal and lignite domestic consumption	Electrification
Algeria	0.3	0.0	0.0	0.0	0.0	0.0	0.7	0.5	0.6	0.0	0.2
Argentina	0.2	0.0	0.1	0.0	0.2	0.0	0.6	0.1	0.9	0.0	0.4
Australia	0.4	0.1	0.0	0.0	0.1	0.2	0.9	0.5	0.8	0.0	0.5
Belgium	0.3	0.0	0.0	0.0	0.1	0.3	0.5	0.4	1.0	0.0	0.4

Indicators / Countries	Energy intensity per unit of GDP	Oil product domestic consumption	Natural gas domestic consumption	Electricity consumption	Renewables share of electricity	Wind/solar power share of electricity	Average CO_2 emission factor	GDP per capita growth (annual %)	Urban population (% of total population)	Coal and lignite domestic consumption	Electrification
Brazil	0.2	0.2	0.0	0.1	0.8	0.0	0.4	0.4	0.8	0.0	0.4
Canada	0.7	0.1	0.1	0.1	0.6	0.1	0.6	0.4	0.7	0.0	0.5
Chile	0.2	0.0	0.0	0.0	0.4	0.0	0.6	0.8	0.8	0.0	0.4
China	0.8	0.6	0.2	1.0	0.2	0.1	0.9	1.0	0.3	1.0	0.4
Colombia	0.0	0.0	0.0	0.0	0.8	0.0	0.6	0.6	0.7	0.0	0.4
Czech	0.4	0.0	0.0	0.0	0.1	0.1	0.7	0.3	0.6	0.0	0.4
Egypt	0.2	0.0	0.1	0.0	0.1	0.0	0.7	0.3	0.2	0.0	0.4
France	0.2	0.1	0.1	0.1	0.2	0.2	0.3	0.3	0.7	0.0	0.5
Germany	0.2	0.1	0.1	0.1	0.2	0.5	0.7	0.4	0.7	0.1	0.4
India	0.4	0.2	0.1	0.2	0.2	0.1	0.7	0.7	0.0	0.2	0.3
Indonesia	0.2	0.1	0.1	0.0	0.1	0.2	0.6	0.8	0.3	0.0	0.2
Italy	0.1	0.1	0.1	0.1	0.3	0.6	0.7	0.0	0.6	0.0	0.4
Japan	0.2	0.3	0.2	0.2	0.1	0.1	0.8	0.5	0.9	0.0	0.6
Kazakhstan	0.8	0.0	0.0	0.0	0.1	0.0	1.0	0.6	0.4	0.0	0.3
Malaysia	0.4	0.0	0.1	0.0	0.1	0.0	0.8	0.7	0.6	0.0	0.5
Mexico	0.2	0.1	0.1	0.1	0.1	0.1	0.7	0.5	0.7	0.0	0.4
Netherlands	0.2	0.0	0.1	0.0	0.1	0.2	0.6	0.2	0.9	0.0	0.3
New Zealand	0.4	0.0	0.0	0.0	0.7	0.8	0.4	0.5	0.8	0.0	0.5

Indicators / Countries	Energy intensity per unit of GDP	Oil product domestic consumption	Natural gas domestic consumption	Electricity consumption	Renewables share of electricity	Wind/solar power share of electricity	Average CO_2 emission factor	GDP per capita growth (annual %)	Urban population (% of total population)	Coal and lignite domestic consumption	Electrification
Nigeria	0.6	0.0	0.0	0.0	0.2	0.0	0.0	0.5	0.2	0.0	0.0
Norway	0.3	0.0	0.0	0.0	1.0	0.0	0.3	0.5	0.7	0.0	1.0
Poland	0.3	0.0	0.0	0.0	0.1	0.1	0.9	0.5	0.4	0.0	0.3
Portugal	0.1	0.0	0.0	0.0	0.4	1.0	0.6	0.0	0.5	0.0	0.5
Romania	0.2	0.0	0.0	0.0	0.3	0.2	0.6	0.6	0.3	0.0	0.3
Russia	0.8	0.2	0.6	0.2	0.2	0.0	0.6	0.7	0.6	0.1	0.3
Saudi Arabia	0.4	0.1	0.1	0.1	0.0	0.0	0.7	0.5	0.8	0.0	0.3
South Africa	0.7	0.0	0.0	0.0	0.0	0.0	1.0	0.4	0.5	0.0	0.6
Spain	0.1	0.1	0.0	0.1	0.3	0.9	0.6	0.1	0.7	0.0	0.5
Sweden	0.3	0.0	0.0	0.0	0.6	0.2	0.1	0.2	0.8	0.0	0.7
Thailand	0.4	0.1	0.1	0.0	0.1	0.0	0.5	1.0	0.2	0.0	0.3
Turkey	0.1	0.0	0.1	0.0	0.3	0.1	0.8	0.6	0.6	0.0	0.4
Ukraine	1.0	0.0	0.1	0.0	0.1	0.0	0.7	0.4	0.6	0.0	0.3
United Arab Emirates	0.4	0.0	0.1	0.0	0.0	0.0	0.8	0.5	0.8	0.0	0.3
United Kingdom	0.1	0.1	0.1	0.1	0.1	0.3	0.7	0.4	0.8	0.0	0.4
United States	0.4	1.0	1.0	0.9	0.1	0.2	0.7	0.5	0.7	0.2	0.5
Uzbekistan	1.0	0.0	0.1	0.0	0.1	0.0	0.8	0.9	0.3	0.0	0.2

Note. GDP – gross domestic product.

The literature review revealed that data mining techniques have become a quite popular method of estimating CO_2 emission levels. In addition, clustering is one of the most common methods used to find hidden patterns in sets of explanatory variables. The items belonging to each cluster are more similar to each other than to those belonging to other clusters. The artificial neural network technique was selected to cluster countries by their CO_2 emission levels for the present study.

This research's objectives required a classification of the selected nations by their potential ability to reduce CO_2 emissions. The Kohonen self-organizing map (SOM) toolkit [36, 37] was selected since it can form homogeneous groups of items and it is considered to be a convenient visual analysis tool for clustering. SOMs are used to classify items and visualize low-dimensional representations of high-dimensional data.

These maps' main feature versus other clustering methods is SOMs' ability to identify an item immediately compared to other approaches based on a specific attribute — locating best and worst items on opposite sides of the map [36, 37]. Kohonen maps are a visual representation of a two-dimensional net of neurons reflecting the organization of the data under analysis (see Fig. 1).

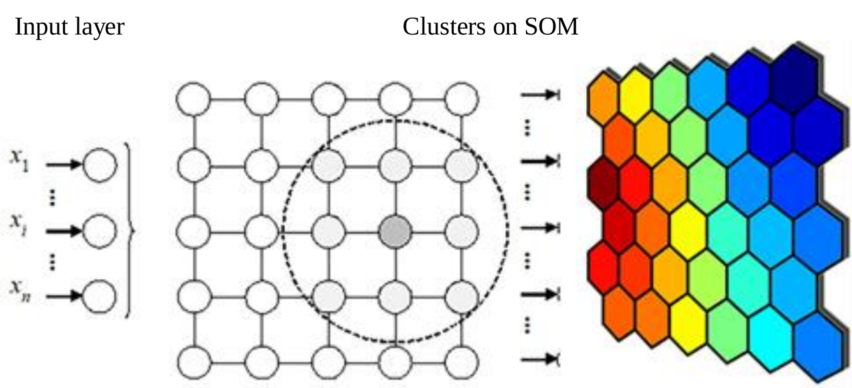

Fig. 1. Visual representation of clusters in Kohonen map [38]

In the present study, clusters of similar countries were formed based on the data collected for indicators such as economic growth, energy consumption, and CO_2 emission level. Eleven key indicators were used to identify as accurately as possible patterns in CO_2 emissions' development and formation. That is, each group's countries have similar values for the indicators that affect their emissions.

Min-max normalization was performed to reduce the excessive influence of variables with large absolute values. Noticeable, that standardized and normalized data set gave us different outcomes of clustering. Through series of experiments we found that clustering with normalized data provided more realistic clusters of the countries than the results based on the original or standardized datasets. The initial map created was thus based on a small number of random variables. This study applied the Gaussian function to determine the neighborhood of neurons for the cooperation process.

The 39 countries were, therefore, clustered according to indicators of energy consumptions, CO_2 emissions, and economic growth by constructing a Kohonen SOM using the Deductor Studio Academic software package. The vectors of 11 values were input into the map of each country's features selected during the 10-year period of 2012–2021, drawing from the data listed in Table 1. The process of creating the map necessarily included finding its optimal dimension (i.e., number of neurons). The SOM's dimension was chosen from various options based on the mean weighted quantization error criterion, which reflects the average distance between the data vectors included in the map's inputs and neuron parameters.

Results

Overall analysis

Several trial runs were conducted based on the chosen indicators of CO_2 emission levels. The results indicate that the 39-country SOM's most suitable structure is a hexagonal grid of 16 by 12 neurons. The clustering was carried out using 7,500 machine learning epochs.

Possible solutions were checked with different numbers of clusters, and the conclusion was reached that the most relevant option has eight clusters. This solution groups nations that exhibit similar decarbonization capabilities and economic growth. The 39 countries were distributed among the eight clusters numbered from 0 to 7. Each group is visually distinguishable by its shape, size, and color (the latter corresponds to a specific number on the scale at the bottom of the Kohonen map in Fig. 2).

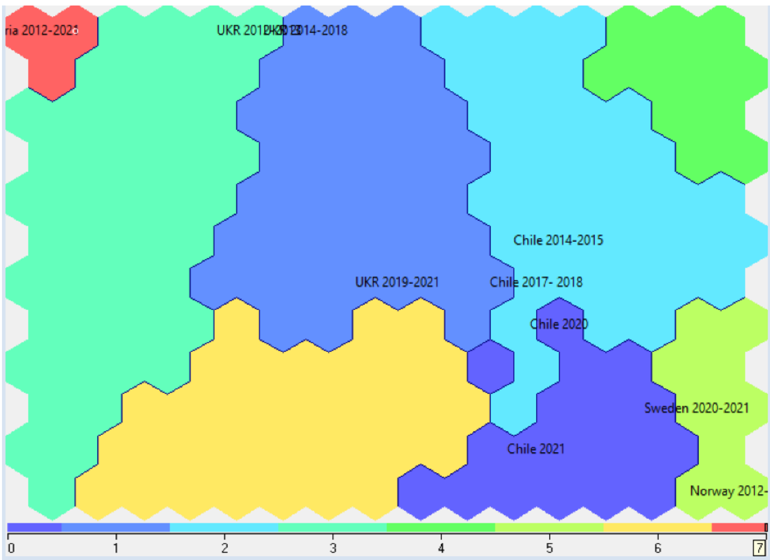

Fig. 2. Kohonen map of 8 clusters from 39 countries based on 3 subsets of indicators for 2012–2021

Table 2 offers a dynamic overview of the countries in each cluster, showing how the map helps track and analyze the nations' evolution over time. For instance, some countries (e.g., the United Kingdom, Chile, and Ukraine) changed their positions various times over the 10-year period. For example, Chile moved from Cluster 1 to 2 and then to Cluster 0, improving its CO_2 emission levels over time. This progress is indicated by Cluster 0's position closer to Cluster 5, which includes countries with the best energy, economic growth, and CO_2 emission values (i.e., ranked as low-carbon economy nations).

Table 2

CLUSTERS IN SELF-ORGANIZING MAP BASED ON 11 INDICATORS FOR 39 COUNTRIES WORLDWIDE FOR 2012–2021

Cluster 0	**Cluster 1**	**Cluster 2**	**Cluster 3**	**Cluster 4**	**Cluster 5**	**Cluster 6**	**Cluster 7**
Portugal (2012-2021)	Argentina (2012-2020)	South Africa (2012-2021)	Algeria (2012-2021)	China (2012-2021)	Norway (2012-2021)	Belgium (2012-2021)	Nigeria (2012-2021)
New Zealand (2012-2021)	Belgium (2012)	Mexico (2020-2021)	India (2012-2021)	United States (2012-2021)	Sweden (2012-2021)	Brazil (2012-2021)	
Spain (2012-2021)	Chile (2012-2014)	Malaysia (2012, 2015-2016)	Indonesia (2012-2021)			Colombia (2012-2021)	
UK (2020)	Czech (2012-2021)	Japan (2012-2021)	Kazakhstan (2012-2021)			Germany (2012-2021)	
Italy (2020)	Egypt (2012-2018)	France (2012-2021)	Netherland (2012-2016)			Italy (2012-2019, 2021)	
Chile (2020-2021)	India (2020)	Egypt (2014-2021)	Poland (2012-2021)			Netherlands (2017-2021)	
	Malaysia (2013-2021)	Chile (2014-2019)	Romania (2012-2013)			Romania (2014-2021)	
	Mexico (2012-2019)	Canada (2012-2021)	Russia (2012-2021)			Turkey (2016-2021)	
	Saudi Arabia (2012-2021)	Australia (2012-2021)	Thailand (2012-2019)			UK (2015-2019, 2021)	
	Thailand (2020-2021)	Argentina (2021)	Ukraine (2012-2013)				
	Turkey (2012-2015)		UAE (2012-2013)				
	Ukraine (2014-2021)		Uzbekistan (2012-2021)				
	UAE (2014-2021)						
	UK (2012-2014)						

From 2012 to 2021, Norway and Sweden had a low level of energy intensity of GDP at consumption, oil products, natural gas and electricity consumption, with the highest renewables and wind and solar power shares in electricity. These two countries were placed in Cluster 5, in the lower right corner of the SOM (see Fig. 2 above and Fig. 3), as they are the most ecologically friendly countries of the 39 nations analyzed.

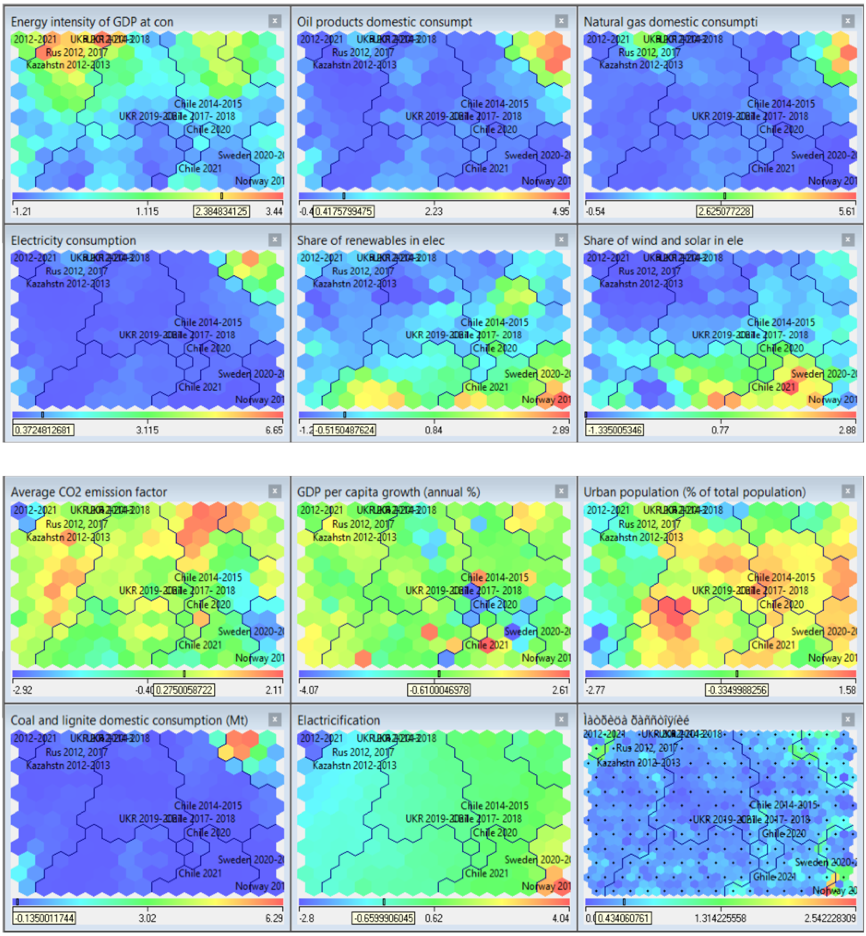

Fig. 3. Kohonen map for 39 countries based on 11 indicators for 2012–2021

Concurrently, Norway and Sweden during this 10-year period had high values for electrification, urbanization, and average growth rate in real GDP per capita, with low levels of coal and lignite domestic consumption and average CO_2 emissions (see Fig. 3 above). The results suggest that Norway and Sweden are leaders in reducing CO_2 emissions and creating climate-resilient economies.

For comparison purposes, Cluster 5 was labeled the leader cluster with the best values for the 11 indicators. All the other clusters can be seen as followers. As mentioned previously, Norway and Sweden are placed as members of Cluster 5 in the lower right corner of the map. The closer a country is to this corner of the SOM, the more highly developed is that nation's use of its decarbonization capabilities and renewable energy sources.

Notably, Cluster 7 has the worst values for all the indicators compared to the remaining clusters, and it is located opposite to the leader cluster on the map (see Fig. 2 above). Up to 2021, the countries that were quite slowly decarbonizing were Nigeria, Algeria, India, and Uzbekistan, which are located in Cluster 7 in the SOM's upper left (see Fig. 2 and Table 2 above).

The Netherlands stayed in Cluster 3 between 2012 and 2016. The results show that this country's slow progress was due to its high average CO_2 emission levels and urbanization. From 2017 onward, the Netherlands improved its position and moved closer to the leader cluster.

Some countries, such as China and the United States in Cluster 4, stayed together in the same cluster for the 10 years. They, therefore, took no steps to improve their decarbonization capabilities over the period analyzed as these countries had and continued to have extremely high CO_2 emission levels.

The SOM developed can be used to determine each nation's best position on the map. All followers may improve their energy and business sectors and identify their potential or current CO_2 emission level to draw closer to the leaders' positions. Progress entails targeting values for the 11 indicators that are closer to Cluster 5 countries' values. For example, further analysis revealed that from 2012 to 2021, Ukraine had approximately an average level of electrification, urban population, CO_2 emissions, and growth rate in real GDP per capita but relatively low levels of coal and lignite domestic consumption (see Fig. 3 above).

Trajectories of movement between clusters

This subsection focuses on Ukraine as case study to analyze its trajectory of movement from one cluster to another. This country's position was examined over the 2012–2021 period, which revealed an overall movement toward a low-carbon economy. In 2012–2013, Ukraine was in Cluster 3, then, in 2014, this nation moved to Cluster 1 and stayed there until the end of 2021 (see Table 2 above and Fig. 4). The most significant leap forward occurred in 2019, when Ukraine became the leader of Cluster 1.

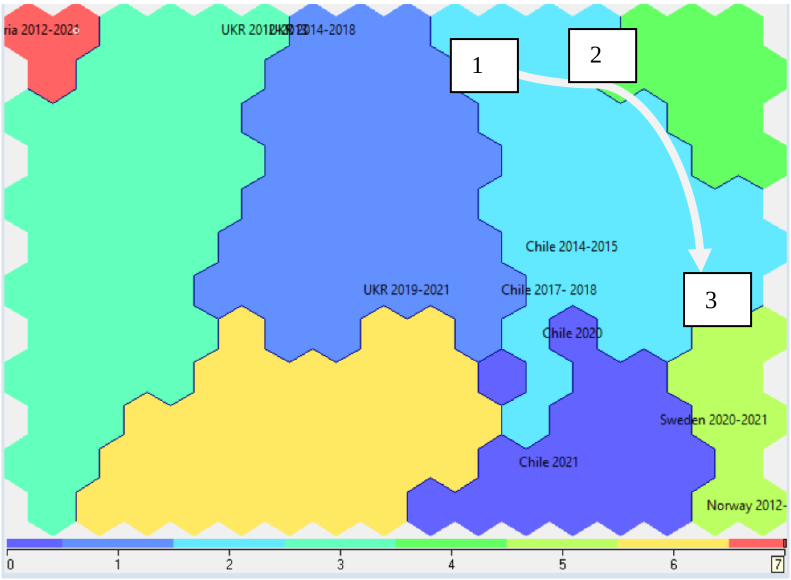

Fig. 4. Ukraine's trajectory of movement between clusters on Kohonen map for 2012–2021

Ukraine's movement between clusters from 2012 to 2021 (i.e., from point 1 to point 3 in Fig. 4 above) was in the right direction, namely, closer to Cluster 5. An analysis of international organizations and public authorities [39-41] was conducted to find an explanation for this trend. Ukraine was dealing with territorial challenges due to the Russian Federation's temporary annexation of the Autonomous Republic of Crimea and city of Sevastopol, as well as anti-terrorist operations in areas of the Donetsk and Lugansk regions in 2014 and 2015. These events dramatically changed Ukraine's development strategies [39]. Due to the conflict, it concentrated on renewable energy so that, in 2015 to 2020, renewables' share in electricity production increased from 7.9% to 11.3%) and energy consumption, GHG emissions, and pollution were significantly reduced in more recent years by applying the following financial and policy measures [40, 41]:

- In 2015, the Ministry of Ecology and Natural Resources of Ukraine developed a National Strategy on the Approximation of Ukrainian Legislation to EU Legislation for Environmental Protection.
- In 2019, the tax on GHG emissions increased four-fold, and, from 2021 onward, the government identified large and medium-sized industrial companies that had to prepare plans for monitoring GHG emissions.
- In July 2020, Ukraine officially supported the European Green Deal, designed to make the European continent climate neutral by 2050.
- In March 2021, the Cabinet of Ministers of Ukraine approved the National Economic Strategy until 2030 for achieving climate neutrality by 2060.

This country's commitment to move toward carbon neutrality implied the identification of a target CO_2 emission level, which requires an efficient, effective, and resilient economy.

The present analysis's findings can help other countries establish benchmarks for improving their own internal decarbonization activities based on other leader nations' strategies and possibly borrowing their best practices for more efficient results. Comparing one country's decarbonization capabilities (i.e., measured by the proposed 11 indicators) to those of leaders can provide hard evidence of whether that nation is competently and successfully engaging in low-carbon activities.

The proposed approach thus uses clustering to identify current and potential CO_2 emission levels to facilitate the formation of low-carbon targets at the national level. For instance, the relevant experts need to review and align Ukraine's net zero emission strategy and CO_2 emission target with the strategies implemented by EU countries in Clusters 5, 0, or 2. The results can help Ukraine to follow historical examples in order to avoid potential mistakes in the decarbonization process and more efficiently bring this nation closer to Cluster 5. Table 3 provides general suggestions for how to move Ukraine more quickly toward a cost-effective, productive low-carbon economy.

Table 3

SUGGESTIONS FOR UKRAINE BASED ON CLUSTERING RESULTS

Target clusters	**Target countries (selected European Union countries from clusters to be followed)**	**Recommendations for how to join target clusters**
Cluster 5	Norway (2012–2021) Sweden (2012–2021)	• Reduce existing domestic fossil fuel assets and, simultaneously, increase renewable energy assets by following Norway and Sweden's example. • Adjust strategies to reduce the absolute values of oil products, natural gas, coal, and lignite domestic consumption indicators. • Move toward increasing the absolute values of renewables' and wind and solar power's share in electricity consumption, as well as of electrification indicators.
Cluster 0 and Cluster 2	Portugal (2012–2021) Spain (2012–2021) France (2012–2021)	• Review current and potential CO_2 emission targets. • Align them with EU countries (i.e., Portugal, Spain, and France), thereby reducing the absolute value of average CO_2 emissions.

Countries' movement between and within clusters is characterized by changes in indicators, such as energy product consumption, and in the outcomes of policies that reduce CO_2 emissions. Nations have moved from one cluster to another by altering their status from high- to low-emission countries and vice versa. Clustering facilitates the identification of each country's level of emissions, whether high or low, for a more accurate identification of that nation's target CO_2

emission level. The proposed approach is based on using the available data on countries to place them in the most appropriate cluster. This method can be used to build a forecasting model of CO_2 emission levels for a group of nations with similar characteristics and development trends.

Conclusions

Accurately identifying target CO_2 emission levels requires appropriate effective mathematical models. This study's first research question (i.e., What are the main country clusters based on national target CO_2 emission levels?) was addressed by developing a new modelling approach to clustering nations by CO_2 emission indicators. The proposed method first segments countries according to the dynamics of a set of 11 indicators, using the Kohonen SOM toolkit. The maps generated facilitate the identification of clusters that are leaders in decarbonization and that should be followed by other countries that are passive participants in the process of lowering emissions. The present analysis's findings include conclusions drawn about the leader cluster, which contains Norway and Sweden, among other nations. The closer a country is to this cluster on the SOM, the more developed and efficient that nation's decarbonization activities are.

The second research question (i.e., How has each country's classification changed over time, with Ukraine serving as an example?) required an analysis of the map created. Ukraine improved its position over the 10 years examined by moving between clusters and drawing closer to the leader cluster. Nations in different clusters were studied to formulate recommendations to help Ukraine foster the most effective transition to low carbon emission levels.

The above results have theoretical and practical implications. The proposed method addresses past research's limitations [27-29] by classifying diverse countries and adding a temporal perspective. This research used Kohonen SOMs to define current and potential CO_2 emission levels in order help countries move in the right direction, namely, toward efficient decarbonization, which has important implications for both academics and policymakers.

Despite this study's significant contributions, the findings are limited by the availability of data for 11 selected indicators in 39 countries over the 10-year period analyzed. In addition, further research is needed to apply this Kohonen map approach at a regional and industry level.

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