Energy Strategy Reviews 50 (2023) 101236

Contents lists available at ScienceDirect

Energy Strategy Reviews

journal homepage: www.elsevier.com/locate/esr

Monitoring the green transition in the power sector with the electricity generation emissions (EGE) tracker

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ARTICLE INFO

Handling Editor: Xi Lu

Keywords:
Composite indicator
Monitoring
Sustainability
Decarbonization
Green transition

ABSTRACT

This paper introduces the Electricity Generation Emissions (EGE) tracker as a new indicator for measuring the decarbonization process associated with the electricity generation mix. The EGE is a composite indicator calculated at the cross-country level on the basis of electricity production of different generation technologies weighted by their corresponding life cycle emission factors. In addition, a four-step methodology is proposed to monitor the energy transition rigorously. It combines index construction and decomposition with the application of machine learning and visualization techniques in a cross-country cluster analysis and temporal mapping. EGE tracker provides a benchmark for comparing countries' sustainability performance in the electricity generation process and quantifies the effectiveness of their climate policies. The design of the index offers a novel measurement to analyze the contribution of each technology to emission reduction.

The application of EGE tracker and the proposed methodology reveals a highly heterogeneous emissions reduction trend across the OECD, indicating that the process of moving away from fossil fuels varies by country and evidences different effectiveness in their climate policies. Moreover, our study highlights the potential for better utilization of renewables and the optimization of sustainable energy mix combinations, paving the way for a cleaner, greener energy future.

1. Introduction

The global recognition of the need to achieve climate neutrality has seen historical momentum as the actions and investments required to achieve the 2050 objectives in terms of green energy generation represent one of the biggest global challenges [1]. Climate neutrality implies achieving net-zero greenhouse gase (GHG) emissions mainly by cutting emissions, investing in clean technologies and protecting the environment.[1] The transformation towards cleaner, competitive and secure energy systems is a prominent segment of energy policy at the cross-country level. Indeed, more than 100 countries have committed to carbon neutrality targets in the aftermath of the COVID-19 pandemic [2]. The decarbonization process has made the traditional business model for companies in the power sector obsolete, particularly for corporations with a greater share of fossil fuels in their energy mix. This is especially relevant for Europe, which has committed under the EU taxonomy to the threshold of 100 gCO_2 e/kWh in the electricity generation process. This represents the average value of power generation

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[1] The goal of climate neutrality in Europe was unveiled in November 2019 with the introduction of the New Green Deal and the roadmap to become a climate Neutral continent by 2050. See https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_en for further details). See also the International Monetary Fund (IMF) document "Group of the twenty: Reaching Net zero Emissions" (available at https://www.imf.org/external/np/g20/pdf/2021/062221.pdf for net zero objectives of the G20 economies and the Long Term strategy of the United States (available at https://www.whitehouse.gov/wp-content/uploads/2021/10/US-Long-Term-Strategy.pdf).

https://doi.org/10.1016/j.esr.2023.101236
Received 7 June 2023; Received in revised form 2 October 2023; Accepted 7 October 2023

emissions between 2020 and 2050 to enable the EU to meet the net-zero by 2050 goal.[2]

Electrifying the economy is a key factor in achieving decarbonization and meeting the net zero emission targets.[3] Because electricity is called to become a new energy vector, monitoring the emissions of the energy mix in the electricity generation process is of paramount importance in order to achieve global climate ambitions. While there is a growing stream of literature that analyzes the effects of the increased reliance on renewable electricity in the context of the green transition (see Refs. [3–6] the analysis of the contribution of energy mix components in the GHG emissions determination process is more limited. Several studies have used energy mix-based measures to proxy the energy component under the Energy-Growth or Energy-Environmental Nexus (see Refs. [7–10]). While these approaches account for the effect of different energy mix components and their contribution to energy intensity, energy security or energy diversification, they do not capture the level of emissions associated with each of the energy mix technologies.

According to [11], monitoring the progress toward sustainable development is an essential matter that has gained widespread recognition. In [12], authors have emphasized the need for transparent monitoring measurements using indicators to achieve a green economy. Composite indicators have proven to be a useful tool in this regard. As an example, [13] propose a Divisia index approach to assess past contributions of different factors to fuel consumption in the electricity sector. They highlight the relevance of using decomposition techniques for the determination of factors affecting changes in sustainable and energy indicators.

Our paper aims to address the absence of information regarding the level of emissions associated with different energy mix technologies. To accomplish this, we propose a composite indicator approach that allows for the quantification of the contribution of each technology to the environmental performance that can be assessed at the cross-country level. The objective is to provide policymakers with a metric that can be used to evaluate the sustainability of the energy systems underlying their policies. The proposed index, denoted as the Electricity Generation Emissions (EGE) tracker, is designed to reflect changes in the energy mix technologies over time. It can be used at a global level as it uses transparent and tangible electricity production data from the International Energy Agency (IEA) Electricity Statistics, as well as National Renewable Energy Laboratory (NREL) factor emission data.

Consequently, we contribute to the current literature by providing the EGE tracker along a four-step methodology for monitoring the energy transition of OECD countries and quantifying the effectiveness of their climate policies. This methodology includes a disaggregation of the index into 'clean' and 'dirty' components combined with graphical analyses to provide valuable insights into the contribution of each technology to a country's generation emissions reduction.

Our results show that the process of moving away from fossil fuels varies by country, suggesting that there is scope for better-exploiting renewables' potential at the global level.

The paper is structured as follows: Section 2 provides a review of the literature focusing on energy-related indicators, presenting the most relevant electricity generation indicators and a summary of the contributions of the proposed EGE tracker. Section 3 contains the methods. Section 4 addresses the results obtained by applying the EGE tracker monitoring methodology to OECD countries. Section 5 discusses the results and links them with the countries' electricity generation policies. Finally, section 6 presents the conclusions.

2. Literature review

In what follows, we provide a review of the literature that addresses sustainability-related indicators. It addresses metrics proposed in academic papers as well as official indicators focused on electricity generation emissions. The purpose is to assess the main limitations of the competing metrics and justify the choice of the proposed indicator. In a second stage, we highlight the innovative characteristics of the proposed EGE metric and its possible applications.

2.1. Review of electricity generation indicators

The need for relevant indicators that can effectively monitor energy policies was previously identified by [14], and many have been proposed in the literature. Authors in [15] provide a deep review of country-level indexes covering broad categories such as power security vulnerability, energy issues and climate change.

Regarding sustainability, academic literature has introduced relevant environmental indicators with different emphases. Some propose advanced frameworks to monitor the performance of different Sustainable Development Goals indicators (see Ref. [16] for an example). Others are focused on efficiency, such as the energy efficiency ratio [17], defined by the prior author as "the ratio between the useful output of an energy conversion machine and the input" (pp. 617), or the exergy efficiency which is based on the same definition but focusing on exergy (see Ref. [17] for an overview of environmental indicators).

When it comes to analyzing the environmental impact of any activity (i.e. electricity generation), the focus often shifts to indicators evaluating the energy mix. For example, the renewable fraction, defined by [17] (pp. 616) as "the proportion of different renewable energy sources in a system". In [8], authors use simple energy mix metrics (derived from International Energy Agency data IEA) that account for the source of primary energy production (which distinguishes between fossil fuels, renewable sources and nuclear plants) as a percentage of total energy production. Most recently, [7] proposed an interpretable energy concentration index to represent the energy mix in a single number and analyzed the diversification process of energy sources at the global level.

While these approaches account for the different energy mix components, they do not capture the level of emissions associated with the mix. Therefore, analysis of sustainable electricity-related indicators often requires the definition of emission indexes usually measured in terms of CO_2 emissions or GHG emissions. In [18], an overview of different carbon emissions indicators is provided and the impacts of CO_2 reductions are analyzed, which are crucial in the decision-making process of market participants and regulators [11,19] Authors in [20] provide a review of energy and carbon intensity indicators, highlighting the lack of deep discussion on the advantages and limitations of the different metrics for monitoring sustainability-related performance.

One natural approach is to create an indicator that measures net emissions directly. This has been used by Ref. [21] or [22] in a decomposition analysis to identify the nature of the factors influencing the changes in CO_2 emissions in China and the European Union, respectively. However, net CO_2 emission indexes fails to measure the efficiency of a country's electricity sector as it focuses solely on the contribution of emissions to pollution, which can be heavily influenced by the size of a given country (and makes cross-country comparisons difficult).

An alternative method requires the adoption of emission intensity indexes, which calculate the ratio between emissions and electricity production. This index has been used in decomposition analyses by Refs. [23,24] as the emission intensity is independent of scale and measures the decoupling of a country's electricity demand from its corresponding CO_2 emissions.

Moreover, several national and transnational energy organisms report emission intensity indicators for electricity generation. The European Environment Agency (EEA) provides the GHG emission intensity

[2] See details in "BRIEFING ON THE EU TECHNICAL EXPERT GROUP'S RECOMMENDATION FOR THE EU TAXONOMY ELECTRICITY GENERATION THRESHOLD," March 2020.

[3] As underlined by Ref. [3]; the increased reliance on electricity in the context of the green transition has enhanced electricity consumption growth in most EU member states over the years.

of electricity generation[4] (previously known as CO_2 intensity of electricity generation), defined as "the ratio of CO_2 emissions from all electricity production, both from public main activity producers and auto producers, against total electricity generation including electricity from nuclear plants and renewable sources". Emissions are taken for both electricity and heat and split proportionally to output according to Eurostat data (the EEA acknowledges this may overestimate electricity generation efficiency). The France transmission system operator (RTE) provides the eCO_2mix,[5] which is "an estimate of carbon-dioxide gas emissions resulting from the generation of electrical power in France, expressed in grams of CO_2 per kWh generated". The United States Energy Information Administration (EIA) also provides information on state-level emissions,[6] defined as "an annual average of CO_2 emissions factors related to total electricity generation by the electric power industry in the United States and in each state". From the methodological point of view, the main difference among these indexes relies on how emissions are measured. Although in all cases emissions are estimated, the approach varies. In some instances, emissions measure come from national-level reports (e.g., EEA's GHG emission intensity of electricity generation), while in others, emissions are calculated by multiplying energy generation by emission factors (e.g., RTE's eCO2mix or EIA's state-level emissions).

From the methodological point of view, using composite indicators can help create powerful energy indexes. Composite indicators condense in a single metric the information from several individual indicators, also known as base indicators. As already stated by Ref. [25], composite indicators are gaining prominence for ranking countries across diverse performance and policy domains. Ref. [26] acknowledges their growing importance in the academic and professional world, as they allow monitoring of qualitative, quantitative, and complex aspects. Other authors, such as [27], identify their potential to attract public attention, facilitate understanding of complex realities, and energize decision-making. Therefore, composite indicators offer social transformation potential but require careful development to prevent them from providing misleading information [28]. A good example on the use of composite indicators within energy-related indexes can be found in Ref. [13], whose composite indicator uses a Divisia index approach [29] to assess the contributions of different factors to fuel consumption in the electricity sector. Another advantage of composite indicators is that they allow to define decomposition techniques, which are widely used to analyze factors that affect changes in environmental and energy indicators (see Refs. [21–24]).

This paper moves further by proposing a time-valued index, built upon the foundation of the aforementioned composite indicator theory, that improves emission intensity indicators available for monitoring energy transition. Moreover, we propose a normalization step as suggested by [7] for building interpretable indexes with a range of values between zero and one. The value we use for the normalization is computed for each country as the equivalent emissions if all the electricity in the given country was produced with the most polluting technology. Therefore, the final index (the EGE tracker) is between zero -representing the best performance scenario: an absolute clean electricity production- and one -representing the worst performance scenario-. This allows for increased index interpretability by quantifying how much each generation technology contributes to emissions but also, quantifying how much each technology contributes in achieving the best (environmental) performance scenario for a given country.

[4] https://www.eea.europa.eu/data-and-maps/daviz/co2-emission-intensity-13/#tab-googlechartid_chart_11.

[5] Eco2mix – CO2 Emissions per kWh of Electricity Generated in France | RTE (www.rte-france.com).

[6] https://www.eia.gov/tools/faqs/faq.php?id=74&t=11.

2.2. *Contribution and innovation of the EGE tracker concerning emission intensity indexes*

In this section, we compare the official benchmark emission intensity indexes provided by national and transnational energy agencies with the proposed index concerning different quality requirements usually found in both industry and academic literature.

Some of the characteristics that allow direct comparison across generation emissions index are the following.

a. Reliability: As indicated in [30], the quality of indicators must be monitored. For this reason, it is necessary to apply official and reliable data sources. This requirement is met by the former emission intensity indexes as well as by the proposed EGE tracker, which uses data from the International Energy Agency (IEA).
b. Frequency: Access to high-frequency data is important to achieve a rigorous monitoring process. In this paper, we aim to overcome the limitations of sustainability metrics, mostly only available at the annual level (see discussion of official indexes below and [31] for a review of the ESG[7]-related indicators). We, therefore, follow [32], who demonstrate that index construction with high-frequency data allows closer monitoring of the underlying conditions. The proposed EGE tracker uses a monthly frequency that can be extended daily as it relies on electricity generation data. In turn, EEA and EIA indexes are provided on a yearly basis, while the eCO_2mix from the RTE is updated hourly.
c. Disaggregation: As indicated by [30], introducing a new metric requires disclosing the main drivers for an overall good or bad performance. Therefore, it is essential that the final composite indicator can be disaggregated into primary components. The EGE tracker can be disaggregated and directly connected to the raw data. For his part, we see under the official sources consulted that the EEA index does not split the efficiency by technology contribution, making it opaque as it cannot be linked to the drivers of the documented efficiency. Finally, the RTE and EIA indexes are easy to trace back to their emission factors and energy generation values, therefore performing well concerning this requirement (it should be noted, however, that RTE's documentation makes the disaggregation process more straightforward compared to that provided by the EIA).
d. Replication at the cross-country level: [33] acknowledge the increasing use of indicators for evaluating cross-country performance while warning of the limitations of such comparisons if the methodology underlying the indicator is not appropriate. The proposed index composition is transparent and replicable, allowing cross-country comparisons. In this paper, the EGE is constructed for all OECD countries included in the IEA data. In turn, the EEA's index is also designed to account for energy efficiency at the cross-country level. In contrast, the EIA's index is only available for the United States (although the granularity arrives at the state level). Finally, the worst-performing index regarding this requirement is the one provided by the RTE since it only applies to France, and its replication to other countries is not straightforward (this requires the generation technologies taxonomy to be homogenized so that common emission factors can be applied at cross-country level).
e. Emissions scope. This requirement applies only to emissions-related indicators. It is crucial to determine the metric applied to measure emissions-related data. Metrics may be constructed considering emissions from direct generation (e.g., the byproducts of coal combustion) or life cycle emissions (e.g., byproducts of coal combustion + all emissions indirectly caused by the generation activity such as plant construction, coal transportation, etc.) The proposed EGE tracker measures all life cycle emissions associated with each technology, while the others do not.

[7] Environmental, Social and Governance.

Table 1 summarises the results of comparing the EGE tracker and the official benchmark indexes concerning the quality requirement presented above.

The analysis presented in Table 1 shows that the EGE Tracker outperforms the alternative benchmarks on most of the characteristics. While the eCO_2mix can be constructed at a higher frequency level, it can only be applied for the case of France and, therefore, cannot be used for cross-country comparison. This positions the EGE Tracker at the forefront of composite indicators for monitoring the sustainability of electricity generation at a cross-country level.

Furthermore, as described in the following sections, the EGE Tracker is an integral part of a four-step methodology for emissions monitoring. This methodology integrates machine learning techniques to facilitate result aggregation and meaningful data interpretation. Consequently, it aspires to create a novel benchmark for assessing the sustainability of countries' electricity generation, advancing the evaluation of OECD nations' energy transition progress, and quantifying the effectiveness of their climate policies.

3. Monitoring methodology through electricity generation emissions (EGE) tracker

In what follows, we delve into the proposed Electricity Generation Emission Tracker indicator for monitoring emissions. Based on the information embedded in the indicator, a four-step methodology for monitoring emissions is derived to monitor a country's generation emissions reduction. The methodology includes a novel disaggregation of the proposed index to account for each technology's contribution to emissions reduction and a proposed quantification method for comparing the emission reduction across countries.

3.1. EGE tracker construction

To guarantee the correct development of the EGE tracker, its construction process has been based on the guidelines provided by the OECD [30], which encompasses normalization, weighting and aggregation.[8]

The indicator is computed according to equation (1):

$$EGE(t) = \frac{\sum_i f_i \, E_i(t)}{f_{coal} \sum_i E_i(t)} \tag{1}$$

where $E_i(t)$ is the quantity of electricity produced (in GWh) at a given time t by the generation technology i in a given country, f_i correspond to the emission factors associated with each technology i and f_{coal} is the emission factor of the coal technology.

Table 1
Comparison of EGE tracker against official benchmark indexes.

	Frequency	Disaggregation	Cross-country replication	Emissions scope
EGE	**monthly**	**Yes (Improved)**	**yes**	**Life cycle**
GHG Intensity	yearly	no	yes	Direct
eCO_2mix	hourly	yes	no	Direct
State-level emission	yearly	yes	no	Direct

Therefore, the EGE tracker base indicators consist of the electricity produced by each technology ($E_i(t)$) and are weighted according to their emission factors (f_i). Then a linear aggregation is applied. The selection of the linear aggregation (which corresponds with a weighted mean) is due to the absolute substitutability[9] (trade-off relationship) documented among reported emissions from different technologies: for instance, the effect of a large number of emissions from natural gas generation can be somewhat neutralized by a small number of emissions from renewable generation.

The output from applying the linear aggregation delivers the non-normalized EGE tracker, which can be interpreted as the GHG associated with the overall electricity production in a given country and corresponds with the numerator of equation (1).

The proposed metric is then normalized. Note that although there is no need to normalize the base indicators composing the EGE tracker given that they are all measured in the same unit [34], we choose to normalize the output obtained from the linear aggregation process to make its interpretation straightforward. The value used for the normalization is computed for each country as the equivalent tons of GHG emitted if all the electricity in the given country was produced with the most polluting technology (i.e., thermal generation with coal) and is represented in the denominator of equation (1). Therefore, the normalization forces the index to lie between 0 and 1, in line with the proposal of [7]. A country with an EGE tracker close to 1 will be defined as highly polluting. In the extreme case, where the EGE tracker takes a value equal to one, all the electricity from the country is generated with coal, the most polluting technology. Meanwhile, a value equal to 0 implies that the country's electricity production sources are 100 % non-polluting.

For obtaining EGE values for a given country, this paper uses two different data sources. The base indicators $E_i(t)$ are obtained from the International Energy Agency (IEA) Monthly Electricity Statistics[10]. The list of technologies follows the new detailed breakdown proposed by the IEA. The list of countries available comprises all the members and associated countries of the IEA.[11]

The values for the different emission factors f_i are obtained from the data set "*Life Cycle Emissions Factors for Electricity Generation Technologies*" ([35]) provided by the National Renewable Energy Laboratory (NREL).[12] This dataset consists of estimates of life cycle greenhouse emissions factors (gCO_2-eq/kWh) built upon NREL's Life Cycle Assessment Harmonization Project.[13] In order to provide reliable and accurate GHG emission estimates for various energy technologies, this project conducted a thorough review and harmonization of life cycle assessments (LCAs). This involved a meticulous process of gathering literature from major databases, scrutinizing them for quality and relevance, and analyzing the data in accordance with strict guidelines. The harmonization process ensured that system boundaries and technical parameters were aligned across technologies, including coal, natural gas, biopower, nuclear, hydropower, wind, and geothermal. By reducing variability in GHG emission estimates, this comprehensive approach offers clearer insights for decision-makers and analysts.

The emission factors dataset provides quartile estimates for different life cycle stages. We have selected the median values for the whole life cycle since it allows us to consider each energy carrier's full life cycle impact, from the extraction/production process to the delivery end-users. In this paper, constant emission factors are considered

[8] Note that imputing missing data and conducting multivariate analysis (commonly used in the construction of composite indicators) were deemed unnecessary due to the absence of missing data in the utilized databases and the conceptual independence of the base indicators (which represent the electricity generated for every distinct technology), thus preventing the need for identifying potential correlations.

[9] See Ref. [50] for more details of the role of substitutability in the aggregation process.

[10] Monthly Electricity Statistics - Data product - IEA.

[11] List of countries available at https://www.iea.org/about/membership.

[12] https://data.nrel.gov/submissions/171.

[13] See https://www.nrel.gov/analysis/life-cycle-assessment.html.

throughout the period studied.

It is worth noting that the taxonomy of technologies of the IEA (which provides the $E_i(t)$ data) does not entirely match the NREL taxonomy (which provides the f_i data). We provide in Table 2 the link between both taxonomies and the corresponding emission factor values, including links to relevant references for the latter in the last column.[14]

Note that the frequency of the index is determined by the frequency of the base indicators, which corresponds with the electricity production data ($E_i(t)$). In this paper, we use monthly electricity production data from IEA since it facilitates the comparison between all IEA's members and associated countries, which is a primary objective of our research. However, the index can be easily extended to the higher frequency case. In addition, the period of study comprises six years, from 2016 to February 2022

Ascan be inferred from Table 2, the value of zero EGE(t) is not feasible under the current low carbon-producing technologies since the emission factors of renewable energies are not strictly zero. This is because we consider the technology emissions throughout the life cycle.

3.2. EGE disaggregation

We have previously stated that the indicator proposed in the paper complies with the "disaggregation" requirement that ensures transparency and traceability. On this basis, we quantify the contribution of each technology to the increase or decrease of the EGE Tracker of a given country.

We define the "dirty" coefficient associated with technology i for a given time t as $C_i^d(t)$, which can be calculated according to equation (2):

Table 2
List of electricity generation technologies and associated emission factors.

Technology (IEA taxonomy)		Technology (NREL taxonomy)	Emission factor (median value, in (gCO_2-eq/kWh)	Reference
COMBUSTIBLE FUELS	Coal	Coal	1001	[36]
	Oil	Oil	840	[37]
	Natural Gas	Natural Gas - Conventional Gas	486	[38]
	Combustible Renewables	Biopower	52	[39]
Nuclear		Nuclear	13[15]	[40]
Hydro		Hydropower	21	[41] (Appendix G)
Wind		Wind	13	[42] (Appendix J)
Solar		Photovoltaic and Concentrating Solar Power	35.5[16]	[43–45]
Geothermal		Geothermal	37	[46]
Other Renewables[17]		Ocean	8	[37]

$$C_i^d(t) = \frac{f_i E_i(t)}{f_{coal} \sum_i E_i(t)} \quad (2)$$

This represents the contribution for technology i to increasing the EGE tracker. In addition, the "clean" coefficient associated with technology i for a given time t, $C_i^C(t)$, is calculated as follows:

$$C_i^c(t) = \frac{(f_{coal} - f_i) E_i(t)}{f_{coal} \sum_i E_i(t)}, \quad (3)$$

which represents the amount in which the EGE tracker is reduced for having a share of energy production generated from technology i instead of coal. This means that if the quantity of energy generated with technology i is produced with coal, the EGE tracker increases by the quantity indicated by $C_i^c(t)$.

It can be easily shown that $\sum_i (C_i^d(t) + C_i^c(t)) = 1$. Therefore, each technology has a "dirty" and" clean "contribution to the EGE (except coal, which has no "clean" contribution). The disaggregation in a "clean" and "dirty" coefficient provides valuable information regarding the contribution of renewable technologies to reducing the EGE tracker and hence, their importance in reducing pollution from electricity emissions.

3.3. Country segmentation based on the EGE tracker

The goal of this section is to group countries together based on their generation mix and EGE values. Clustering enables us to categorize countries into meaningful groups where members of each group share more similarities with each other than with countries in other groups. This helps us better understand the similarities and differences between countries in terms of their electricity generation and emissions.

For this purpose, we use the data provided by IEA corresponding to the electricity generation of a set of 47 countries on a monthly frequency. Therefore, we have a panel of 47 countries with 74 monthly observations from January 2016 to February 2022. For each observation within the panel (i.e., observation corresponding with a certain country and month), we have ten generation-related variables (energy generation by each technology reported in Table 2) and the corresponding EGE tracker.

In order to cluster the data, the panel is aggregated on a yearly level. For each country, the annual average EGE value and the yearly average production generation for each technology are calculated. As the generation of "other renewables" technology is very limited across countries, this variable is not considered relevant for grouping countries and has been discarded.

The segmentation is then performed using a k-means clustering algorithm. Variables are centered and scaled for the clustering, and the selection of the number of groups is performed by exploring the clustering results of different numbers of groupings and selecting the best number according to a trade-off between quantization error and the number of clusters [47].

3.4. Temporal mapping of EGE tracker

In this section, we resume the information on the EGE evolution over time into relevant features that allow an improved comparison among countries. Hence, the EGE time series can be decomposed into the following three representative features.

a) Average level of the EGE tracker: This feature is calculated as the average of the EGE tracker over the period analyzed. It indicates the overall quantity of pollution generated by the mix during the period, which allows the classification of the countries according to the pollution level.

[14] Note that categories included by IEA "other combustibles" -within combustible fuels- and "not specified" have not been included in the index since we have not found associated emission factors; nevertheless, the percentage of electricity production associated with these technologies is residual.

[15] This value is for nuclear technology with light water reactors (the most common type of nuclear reactors).

[16] This value is the mean between solar photovoltaics and solar thermal.

[17] Defined as "electricity generated from tide, wave, ocean and other non-combustible sources".

b) Linear trend of EGE tracker: This feature is the slope of the linear trend of the EGE time series. The trend for a given country is calculated by regressing the time series EGE values of the country with respect to the time trend, i.e., $EGE(t) = \beta_0 + \beta_1 t + \varepsilon$. The linear trend is defined as the slope coefficient β_1 estimated. The linear trend approach allows cross-country comparison of emission reduction strategies. In this paper, the slope is scaled so that the estimated value represents units of "increments of EGE per year".
c) Volatility of EGE tracker: The volatility is calculated as the standard deviation of the residuals of the linear trend regression. Hence, the EGE volatility measures the variability in the time series evolution of the index with respect to the linear trend extracted, representing the degree of flexibility or sensitivity concerning weather or other seasonal changes.

4. Results

This section presents the results of the proposed methodology following the approach described in Section 3. Results are structured in two sub-sections. Firstly, the EGE tracker is used to analyze the first two methodological steps (EGE tracker construction and EGE disaggregation) applied to a group of selected countries, aiming to demonstrate its usefulness in providing a clear evaluation of a country's energy mix contribution to electricity generation emissions and its connection to energy policy. We also show how the disaggregation of the index gives important information regarding the extent and evolution of the efficiency (or flexibility) provided by a given energy mix. Secondly, the index is used for a global cross-country comparison based on the last two methodological steps (country segmentation and temporal mapping).

4.1. EGE index and disaggregation

This section analyses the differences in the EGE tracker exhibited at the cross-country level. On the one side, the EGE tracker can be compared directly among countries, as seen in Fig. 1, which shows the evolution of the EGE tracker for some European countries (Spain, Germany, Poland and France) and the EU benchmark. The latter is obtained from a weighted mean of the EGE tracker of all the EU member countries present in the IEA, where the weight of each country corresponds with its share of energy production (in unitary percentage) to the total energy production in the EU.

We can see remarkable differences in the time series evolution of the different countries. While Germany and Spain have somewhat similar pollution levels with an overall decreasing trend, France and Poland lie in the graph's lower and upper parts, respectively. On the one hand, Poland is the worst performing country with EGE values of around 0.75, implying that its emissions from electricity generation are equivalent as if 75 % of its electricity were generated by coal technology (and the other 25 % by completely clean technology). On the other hand, France is clearly outperforming the EU benchmark with EGE values around 0.1, implying that the Energy mix is equivalent to having 10 % electricity generated by coal and the rest by clean energy. The efficiency of the Spanish energy mix is, on average, higher than that of EU benchmark while Germany, on the other hand, slightly underperforms the EU benchmark.

Fig. 1 is useful for identifying the evolution of the overall emissions in the country, however, it does not provide relevant information about the factors or technologies affecting the reduction in emissions. The disaggregation coefficients defined in step two of the proposed methodology can be calculated for that purpose. Therefore, the EGE tracker for each country can be decomposed to show the pollution contribution of the different generation technologies. This decomposition is illustrated in Fig. 2, which depicts the EGE tracker represented by a dashed line. The areas below the dashed line - with the "dirty" suffix in the legend - measure each polluting technology's contribution to the index (note that the EGE tracker is zero if the associated energy mix is 100 % clean). The areas above the dashed line -with the "clean" suffix in the legend-indicate how each technology that is less polluting than coal contributes to the index reduction.

For example, natural gas is illustrated with an intense orange area below the dashed line and labeled as "*N. Gas (dirty)*." This area indicates how much it contributes to increasing the EGE tracker (with respect to its minimum value defined as zero). Natural gas is also represented by a light orange area labeled as "*N. Gas (clean)*." This area corresponds to the

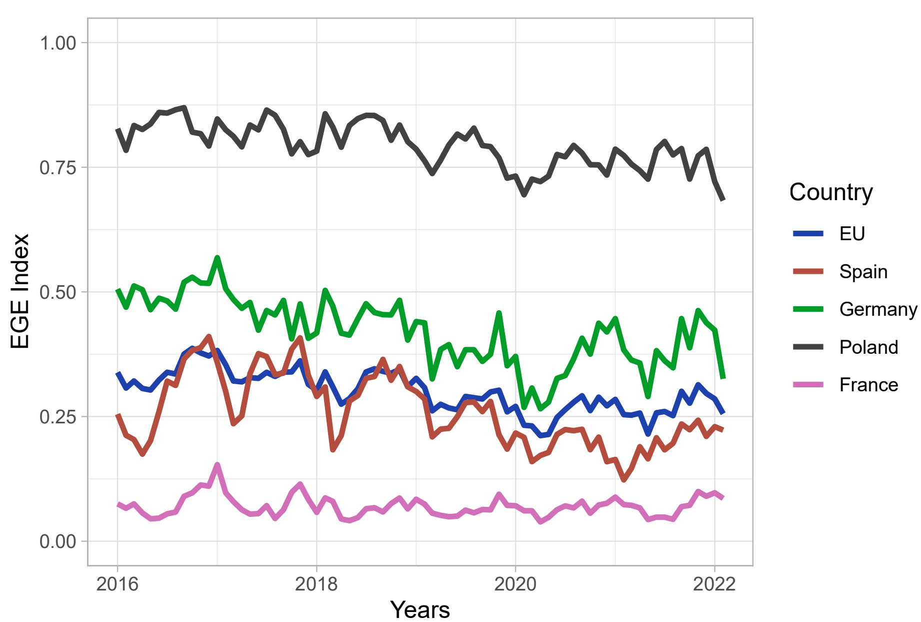


Fig. 1. EGE tracker for Spain, France, Germany, Poland and the EU benchmark.

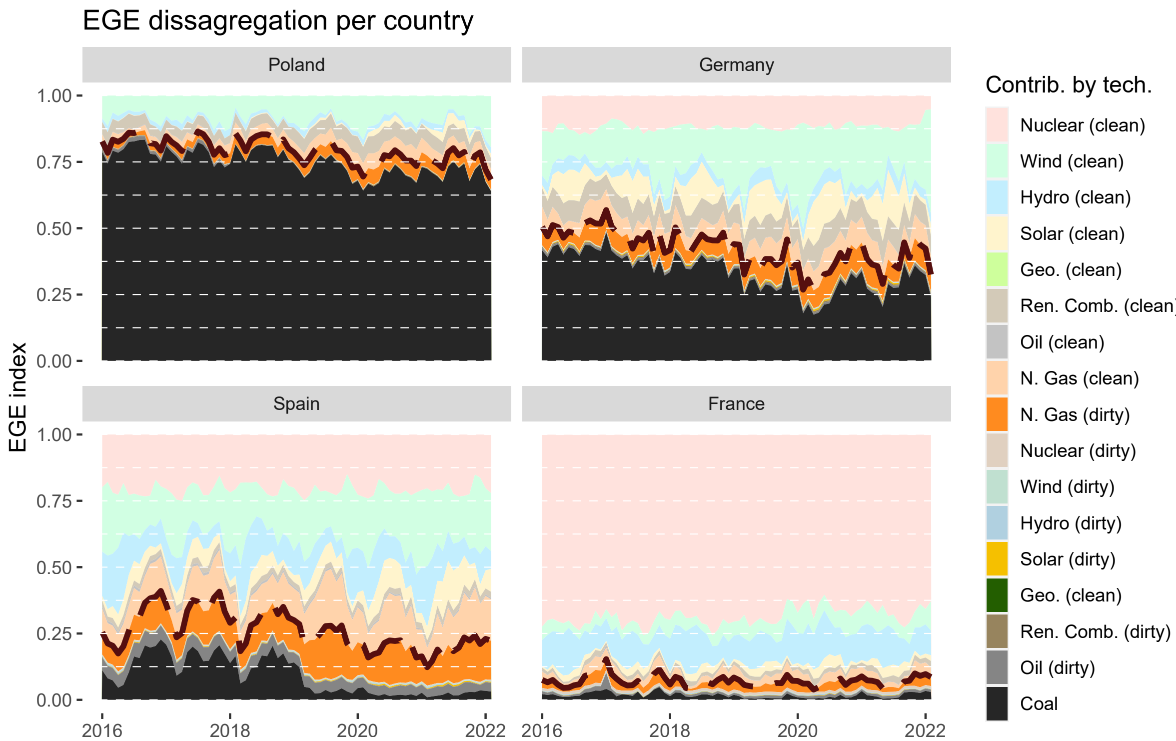


Fig. 2. Disaggregated EGE tracker for Spain, France, Germany and Poland.

amount in which the EGE tracker is reduced for having a share of production generated from natural gas instead of coal. Therefore, for the same amount of energy produced, the less polluting the technology, the larger the area above the dashed line and the smaller the area defined below it. This is clearly seen in the cases of nuclear and renewable technologies. Finally, coal is only represented by an area below the dashed line as it is the most polluting technology.

A close look at Fig. 2 shows that the cross-country energy mix at the European level is highly heterogeneous. One of the main drivers for reducing the EGE tracker and, therefore, emissions is substituting generation with coal by other technologies. In Germany, wind generation has exhibited the most substantial growth (Germany's commitment to the energy transition and its increased reliance on renewables has been addressed by Ref. [12]. In the case of Spain, coal production was drastically reduced in 2019, substituting it with natural gas, together with a gradual deployment of renewable sources, such as wind and solar (the evolution of the energy mix in the Spanish case is addressed by Ref. [3]. It is also evidenced that when renewable technologies (mainly wind, hydro and solar) exhibit a higher contribution to the energy mix, the value of the index decreases and vice versa. The minor variations in the EGE of France and Poland through the studied years are due to their significant reliance on a single technology: nuclear in the case of France, which makes it have a very low EGE and coal in the case of Poland, which makes it have a very high EGE. Nevertheless, it must be acknowledged that Poland is slightly reducing its generation with coal thanks to the increasing (although still minor) use of cleaner technologies (natural gas, renewable combustibles, wind and solar). Finally, the consequences of the energy crisis under a post-COVID recovery and the extreme weather conditions are also reflected in this figure, especially for the case of Spain and Germany, which show an increase in pollution from 2021 driven by a higher reliance on coal and gas. A close look at these figures suggests that, in the case of Spain, a lower hydro generation made gas even more necessary despite the high prices and supply constraints arising from the war in Ukraine.

The disaggregated EGE tracker for all countries considered is reported in Annex I.

4.2. *Segmentation and temporal mapping for global cross-country comparison*

While the time series and disaggregation plots deliver very detailed information, it is important to identify differences in the evolution of the EGE tracker between a broader set of countries. To facilitate this broader comparison, we perform the country segmentation explained in section 3.3, considering the sample of OECD countries.

The country segmentation classifies the different OECD countries in terms of their energy mix, providing a total of six clusters. Fig. 3 reports the cluster results in a matrix of bar plots representing every group. Bars are plotted for each technology and EGE variable, whose height is calculated as the average value for the set of countries assigned to the cluster. As the variables were centered and scaled, a value of zero in a bar implies that the mean value of the variable for the countries in the cluster is equal to the average value for all countries considered. When the mean value is at least one standard deviation away from zero, the bar is colored in red, meaning that the cluster is characterized by significantly higher (or lower) values of the corresponding variable.

Upon analyzing the figure, we proceed to describe the key characteristics of the six clusters as follows.

- Cluster 1 (Hydro) represent countries with a significantly low EGE value and high Hydro and Geothermal production in the mix.

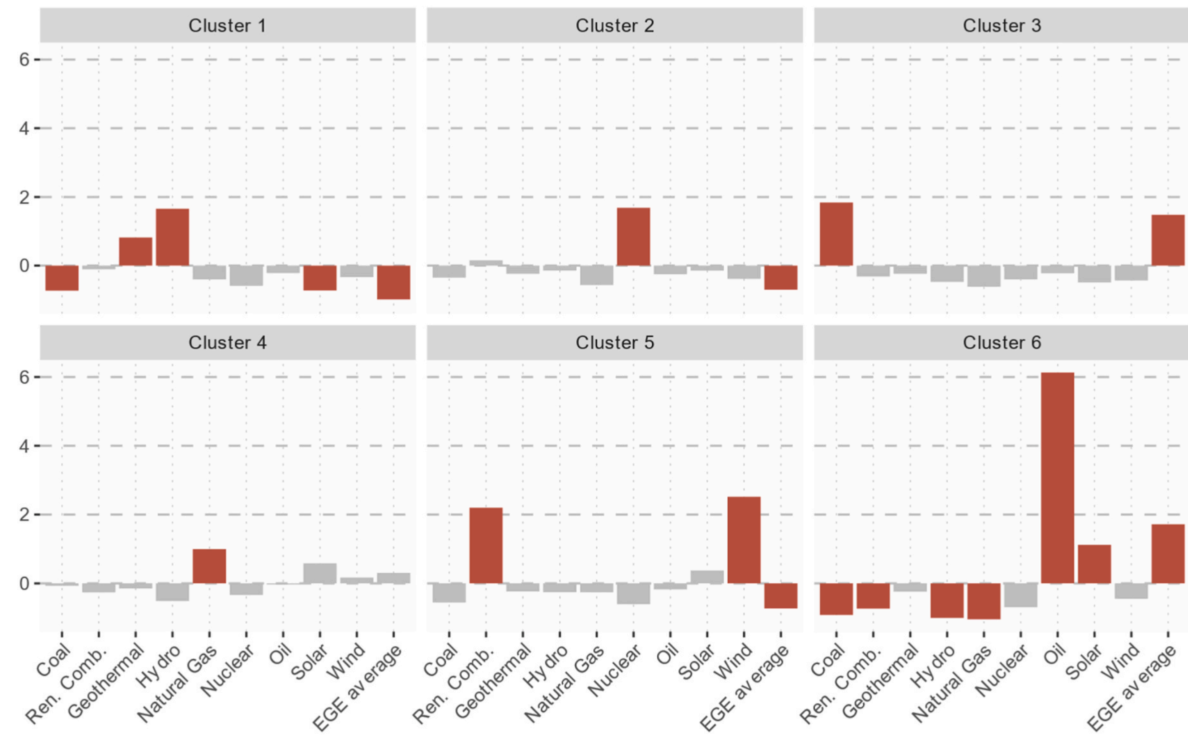


Fig. 3. Relevance of the features for each cluster. A value of zero in a bar implies the mean value of the variable for the countries in the cluster is equal to the average value for all countries considered. Significant features for each cluster are marked in red. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

- Cluster 2 (Nuclear): Countries with a significantly low EGE value and high Nuclear production in the mix.
- Cluster 3 (Coal): Countries with a significantly high EGE value and high Coal production in the mix.
- Cluster 4 (Transition): Countries characterized by an average EGE value and average values in most technologies. It is, however, the case that Natural Gas production has a dominant role due to the following two reasons: *a)* it is the leading technology in some of the countries that belong to this cluster, such as Italy, Mexico and the Netherlands; *b)* it is an essential part of a diversified energy mix. As shown, this cluster exhibits the most significant decrease in EGE, underlining the role of natural gas as an Energy source for the transition. For this reason, we have labeled this cluster as the "transition" cluster.
- Cluster 5 (Wind): Countries with a significantly low EGE value and high Wind and Renewables production in the mix.
- Cluster 6 (Oil): Countries with a significantly high EGE value and high Solar and mainly Oil production in the mix.

Table 3 reports the list of the different countries analyzed and their corresponding cluster. Many countries are classified under the same cluster for every considered year. In those cases, only the name of the

Table 3
Table of countries assigned to each of the clusters. Numbers in parenthesis indicate the number of years the country has been assigned to the corresponding cluster. If no number is shown, the county has been assigned to the corresponding cluster for the six years of study.

Cluster 1 (Hydro)	Cluster 2 (Nuclear)	Cluster 3 (Coal)	Cluster 4 (Transition)	Cluster 5 (Wind)	Cluster 6 (Oil)
Austria	Belgium	Australia (3)	Australia (3)	Denmark	Cyprus
Brazil	Bulgaria	Chile (1)	Argentina	Estonia (1)	Malta (1)
Canada	Czech Rep. (3)	Czech Rep. (3)	Chile (4)	Lithuania	
Colombia	Finland	Estonia (5)	Germany	Luxemburg (3)	
Croatia	France	India	Greece	Portugal (1)	
Iceland	Hungary	Korea (4)	Ireland	U·K. (2)	
Latvia (4)	Romania (2)	N. Macedonia	Italy		
Luxemburg (3)	Slovak Rep.	China	Japan		
New Zealand	Slovenia	Poland	Korea (2)		
Norway	Sweden	Serbia	Latvia (2)		
	Switzerland		Malta (5)		
			Mexico		
			Netherlands		
			Portugal (5)		
			Romania (4)		
			Spain		
			Turkey		
			U·K. (4)		
			United States		

country is shown. For those cases in which different years have been assigned to different clusters, the number of years assigned to each cluster is written in parentheses.

The next step is to resume the information on the EGE time series to achieve an improved comparison among countries. With this aim, we apply the temporal mapping presented as the fourth step of the methodology (see Section 3.4). Therefore, the EGE features -average level, linear trend and volatility-are obtained for all countries over the six years analyzed.

In order to illustrate the values obtained for each feature, the countries depicted in Fig. 1, are analyzed. The analysis of the average level of the EGE tracker shows that France clearly has the cleanest generation mix in terms of CO_2 resulting in an average EGE of 0.07, while Poland exhibits the most pollutant mix with an average calculated EGE tracker of 0.79 over the period considered. Germany and Spain lie between France and Poland, with average EGE values of 0.42 and 0.26, respectively. Results related to the linear trend show an estimated coefficient for France of −0.001 (i.e., a reduction of 0.001 units in EGE per year). Poland and Spain exhibit linear trends equal to −0.017 and −0.023, respectively. Hence, their average yearly reduction is significantly more pronounced than that estimated for France. However, Germany presents a linear trend of −0.027 average yearly reduction, showing the greatest improvement in the generation mix for reducing pollution compared to Spain, Poland and France. Finally, the analysis of the volatility of the EGE tracker shows that France exhibits an EGE volatility of 0.020, followed by Poland, which exhibits a volatility of the EGE tracker of 0.032. This suggests that the reliance on nuclear and carbon technologies delivers greater system stability. Higher reliance on renewables leads to higher volatility, as is seen in the case of German and Spain, which exhibit EGE volatilities of 0.049 and 0.058, respectively.

Fig. 4 combines the different clusters obtained with their corresponding estimated features. It illustrates a scatterplot that combines the Average EGE feature (y-axis) with its Linear Trend feature (x-axis). Each country is colored according to its most frequently assigned cluster. In addition, vertical lines represent the EGE volatility feature for each country.

The plot allows us to visually identify the effectiveness of the emission reduction strategies of each country in comparison with cluster and non-cluster counterparts. Countries plotted on the top of the graph exhibit higher EGE average values (i.e., more pollutant countries), while countries on the bottom are the ones with fewer emissions in electricity generation. Moreover, the countries present different evolution of pollution reduction, as seen by the wide range of the slope coefficients shown in the x-axis. Countries on the left of the graph, with negative values of the Linear Trend Coefficients, are those that evidence a greater reduction trend in their emissions. Countries with Linear Trends close to 0 show that the EGE tracker has not changed significantly over time, while countries with positive trends imply that the EGE tracker has increased in the study period.

Analyzing the position of each country across the scatter plot provides meaningful information regarding the effectiveness of the electricity policies of each country, as will be discussed in the following section.

5. Discussion

Fig. 4 aggregates the information on every country's energy mix and illustrates the evolution of emissions as reflected in the EGE tracker. While the EGE level and evolution vary significantly across countries, several insights can be extracted from the different clusters.

5.1. Coal and Oil clusters

The top of the graph is populated with countries belonging to Coal and Oil clusters, with Average EGE values over 0.6. These are the

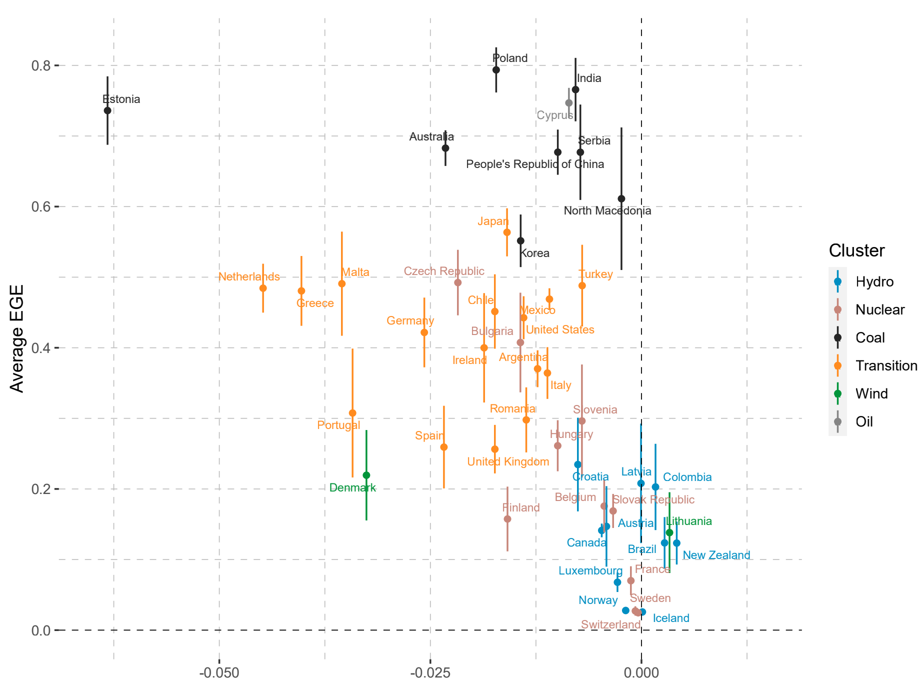


Fig. 4. Average EGE vs. Linear Trend Coefficient. Vertical lines represent the volatility of EGE.

countries with high emissions; however, significant differences are observed in EGE trends. While most of these countries exhibit EGE reductions, Estonia stands out for achieving the highest emission reduction, reaching a remarkable trend of −0.075 EGE/year. This differs from countries like India, which exhibits a similar Average EGE level with a much lower reduction over time (−0.01 EGE/year). Indeed, Estonia has implemented several policies for significantly reducing its dependency on coal and has set a target to reduce greenhouse gas emissions by 80 % by 2050 compared to 1990. To achieve this goal, the policies promote the increased use of renewable electricity sources up to 40 % share of total energy consumed and energy efficiency measures [48]. This analysis can be complemented by looking at the EGE disaggregation plot in Annex I, which shows how Estonia has achieved EGE reduction in recent years by substituting coal with renewable combustion. Therefore, the initiatives are clearly contributing to the emission reduction in electricity generation.

In a parallel strategy, India has set a target to reduce the carbon intensity of its electricity sector by 33–35 % by 2030 compared to 2005 levels and has implemented several policies to support the development of renewable energy, including a national target of achieving 175 GW of renewable energy capacity by 2022. However, as illustrated by the EGE trend coefficient, the policies have had a mild impact on emission reductions. Looking at the disaggregation plot, India presents a shared generation mix of mainly coal and hydro, but its evolution is not changing over time.

It is also worth analyzing the volatility component. India and North Macedonia rely heavily on coal with significant contribution of hydro technology. However, the seasonal behavior is very different, as evidenced by the volatility component of the EGE for these countries. Looking at the disaggregation plots, it can be observed that India has a very regular seasonal component, hence, low volatility. On the other hand, North Macedonia exhibits very high volatility with extreme variations in hydro production. The proposed analysis can therefore help identify countries sensitive to seasonal variations.

5.2. Transition and Wind clusters

Countries belonging to the Transition and Wind clusters are plotted around the level of average EGE and average slope. Both groups exhibit a wide range of Linear Trends, ranging from slopes of −0.01 up to −0.045 (except Lithuania, with a positive slope). We can see how the Netherlands and Greece exhibit the greatest reductions in EGE because of the active politics for reducing generation. Indeed, The Netherlands' Climate Policy Plan 2019 aims to reduce greenhouse gas emissions by 49 % by 2030 compared to the 1990 level. The policy emphasizes the importance of decarbonizing the electricity sector by increasing the share of renewable energy sources and phasing out the use of coal for electricity generation. Similarly, Greece's 2021-2030 National Energy and Climate Plan sets a target of reducing greenhouse gas emissions by at least 55 % by 2030 compared to the 2005 level. The policy aims to decarbonize the electricity sector by increasing the share of renewable energy sources, especially wind and solar power ([49]). As shown by the EGE tracker, these policies are clearly impacting emission reductions positively. Turkey, in turn, shows an equivalent average EGE value but with lower emission reductions due to less active decarbonization policies.

It is worth noting how countries under the Transition cluster exhibit greater trend reductions than the remaining clusters, evidencing that these are countries involved in a greater compromise in emission reductions.

5.3. Nuclear and Hydro clusters

Finally, Nuclear and Hydro clusters are represented in the lower part of the Average EGE axis. We can see that the EGE trends in these countries are significantly closer to zero. In fact, some countries have even seen a slight increasing trend in their EGE levels. This is consistent with the fact that when the Average EGE is already low, there is less capacity to account for significant EGE reductions.

Regarding volatility, it is worth noting that countries such as Canada, Norway, Iceland, and Switzerland show shallow EGE values. This indicates a remarkably stable generation mix primarily driven by a reliance on two or more clean technologies that complement each other (hydro and nuclear being the predominant ones in this cluster). It is worth noting that, among all renewable sources, hydro generation allows for the most effective modulation of the generation mix through energy storage using reservoirs. In contrast, other clean technologies, such as wind or solar, have very limited storage capabilities, which is translated into higher volatility (i.e., the cases of Spain or Germany, with clean production more dependent on wind and solar technologies). Therefore, the results provided in this section demonstrate that the proposed methodology, based on the clustering and mapping of the EGE features, is a valuable and useful tool for monitoring emissions reduction policy efficacy at the cross-country level.

6. Conclusions and policy implications

Governments and market participants across the globe need tools to track the energy transition process and evaluate the effects of the energy policies that are applied to achieve the desired climate neutrality. This monitoring must be made with neutral, transparent, and rigorous measurements that can help policymakers to make the appropriate decisions in supporting the decarbonization of the economy.

Electricity is vital in the green transition as it will play a central role in building a decarbonized and secure future. In this paper, we introduce the EGE tracker, a composite indicator to monitor the decarbonization of the electricity generation sector. The proposed index is constructed to measure the evolution of emissions at the cross-country level. It is based on the electricity generation mix and emission factors. Along with the proposed data-based methodology for analyzing the evolution of the tracker, a comprehensive comparison across countries through clustering analysis is provided. It has been carefully designed to comply with benchmark quality requirements, namely identified as frequency, reliability, disaggregation, and cross-country replication. Moreover, to our knowledge, it is the only index that accounts for life cycle emissions in electricity generation and measures the contribution of technologies to reducing emissions. It, therefore, outperforms most official indicators provided in the literature and national and international energy organizations.

The performance of the EGE tracker has been tested empirically in an analysis comprising the OECD economies covered by the EIA electricity generation data. Our main results and the corresponding policy implications are summarized as follows.

First, the cross-country comparison of the EGE tracker shows that the combination of energy sources used for power generation varies greatly across OECD countries. On one extreme, we have countries with very low EGE values due to the principal role of hydro, wind and nuclear such as Norway (almost full power generation with hydro), Iceland (hydro as the primary source and wind as the secondary source) or Switzerland (hydro as the primary source and nuclear as the secondary source). Conversely, countries with extremely high EGE values rely heavily on coal production. The most representative example of this latter group is Poland, the most polluting country.

Secondly, the two last steps from our monitoring methodology provide six clusters of countries that facilitate the analysis of the energy transition across the OECD economies. These groups have been labeled as Hydro, Nuclear, Wind, Transition, Oil and Coal clusters, each one with different characteristics. The Hydro, Nuclear and Wind clusters present, on average, the lowest EGE values and exhibit a low reduction in emissions. This result arises because the absolute dominance of renewable sources has allowed these economies to become very low carbon emitting in their power production mix, leaving limited room for further improvement. The Transition cluster exhibits intermediate EGE values and a high reduction in emissions. Countries that belong to this group are on a clear decarbonization path in which natural gas plays an important role as a vector of the energy transition. Finally, the most polluting clusters are those dominated by oil and coal. They present the highest EGE values while facing a large room for improvement in the emissions reduction process.

Our analysis concludes that the emission reduction policies are highly heterogeneous within Europe and across OECD economies. While many countries have been making progress in their energy transition away from fossil fuels, others are still dependent on them as their primary source of electricity generation. The proposed tracker and methodology can provide relevant information to assess whether a country's policy has been effective or to help designing better policies by comparing strategies across countries.

Finally, future EGE tracker application extensions include monitoring the net zero goal defined under the average 100 gr of CO_2 per kWh of energy produced up to 2050. Moreover, the index accounts for life cycle emissions in electricity generation, making it a relevant monitoring tool as we offer a holistic view of the generation emissions.

CRediT authorship contribution statement

J. Portela: Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **D. Roch-Dupré:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Project administration. **I. Figuerola-Ferretti:** Conceptualization, Validation, Resources, Writing – original draft, Writing – review & editing, Supervision, Funding acquisition. **C. Yéboles:** Conceptualization, Methodology, Software, Writing – original draft. **A. Salazar:** Conceptualization, Methodology.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used ChatGPT in order to improve readability and language. After using this tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The databases used in the paper are public and their links are provided

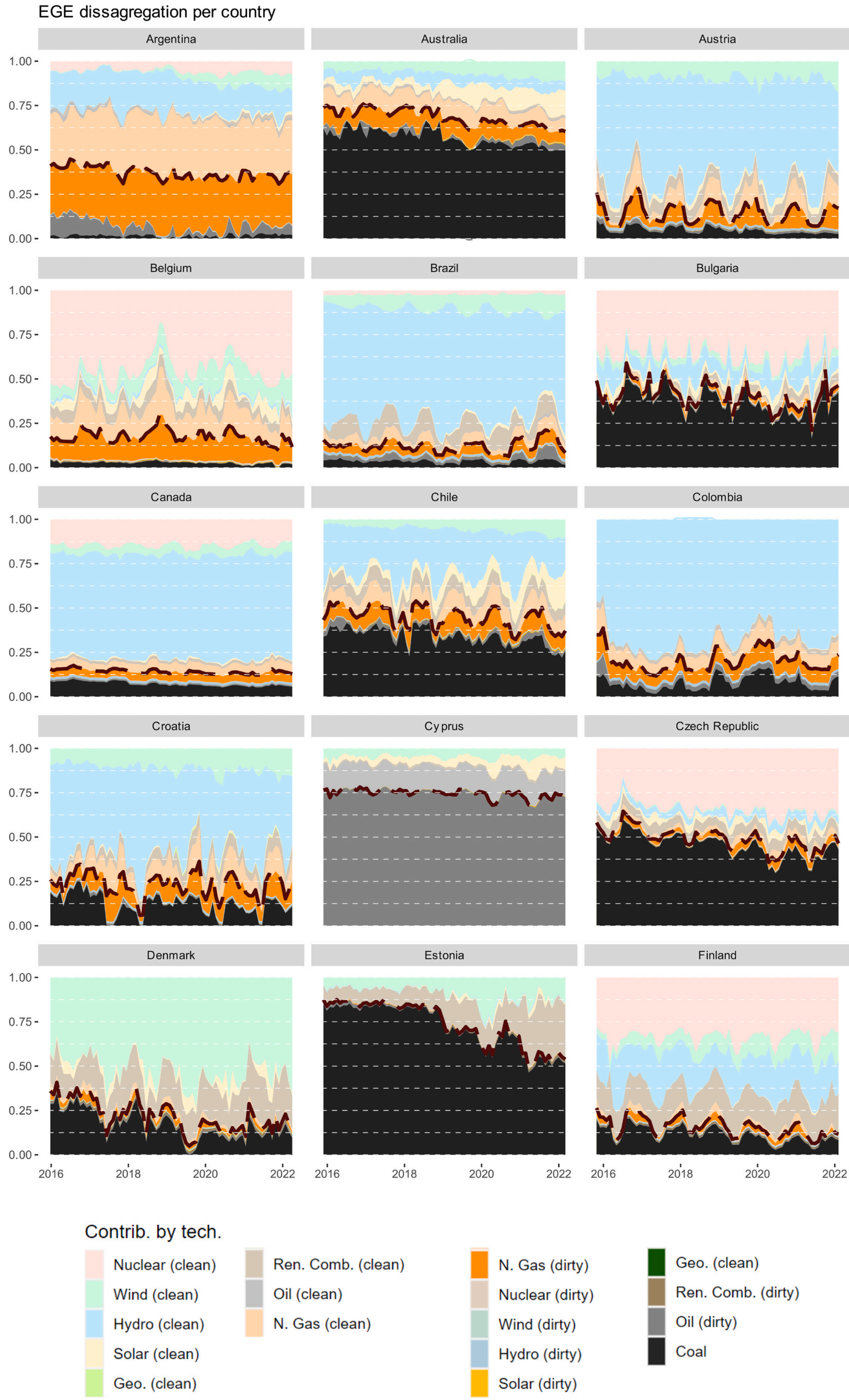
Acknowledgments

We would like to express our deepest gratitude to all those who have contributed to this scientific paper, especially to the 360 Smart Vision initiative from ICADE (current "Observatorio Criteria"), which provided funding and resources to carry out this study.

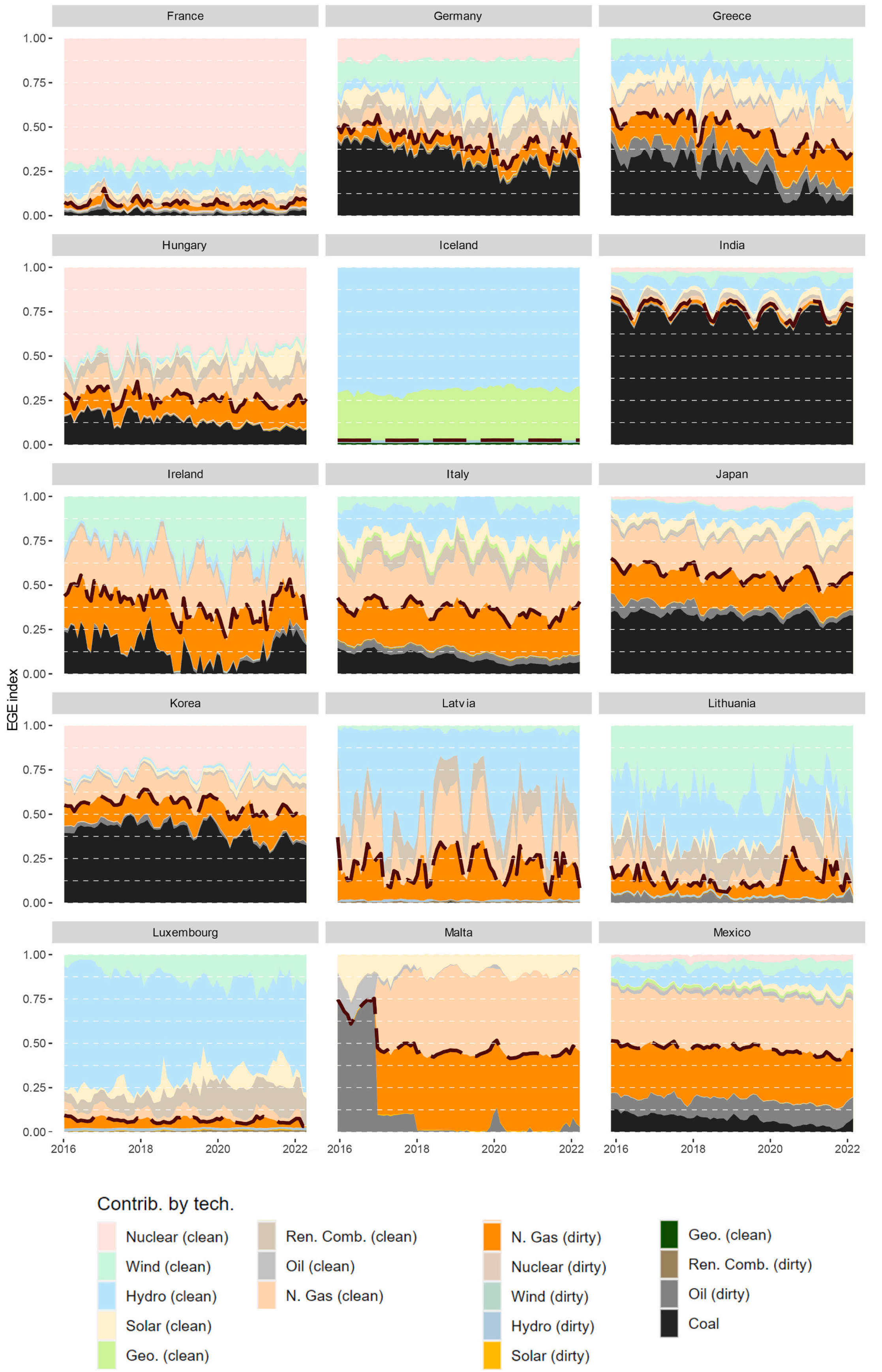
We would also like to thank Joaquin Chico Cespedes for his helpful comments and the seminar participants from Smart Vision who contributed to the literature review.

This project has been partially funded by Universidad Pontificia Comillas (*Financiación Proyectos de Investigación Propios 2020)*.

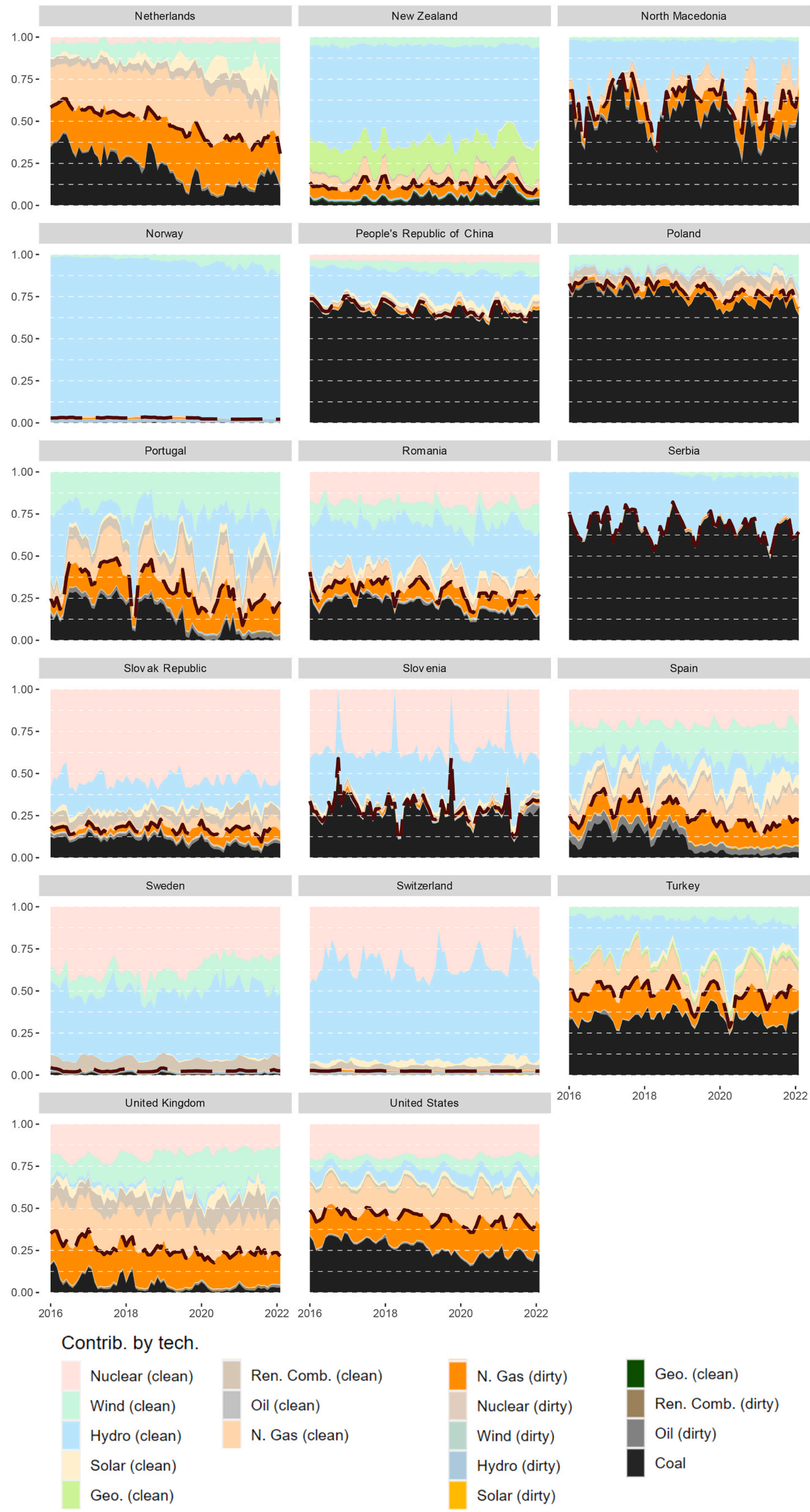
Annex 1



ANNEX: EGE dissagregation per country.


France
Germany
Greece
Hungary
Iceland
India
Ireland
Italy
Japan
Korea
Latvia
Lithuania
Luxembourg
Malta
Mexico
EGE index
1.00
0.75
0.50
0.25
0.00
2016
2018
2020
2022
Contrib. by tech.
Nuclear (clean)
Wind (clean)
Hydro (clean)
Solar (clean)
Geo. (clean)
Ren. Comb. (clean)
Oil (clean)
N. Gas (clean)
N. Gas (dirty)
Nuclear (dirty)
Wind (dirty)
Hydro (dirty)
Solar (dirty)
Geo. (clean)
Ren. Comb. (dirty)
Oil (dirty)
Coal

. (*continued*).


Netherlands
New Zealand
North Macedonia
Norway
People's Republic of China
Poland
Portugal
Romania
Serbia
Slovak Republic
Slovenia
Spain
Sweden
Switzerland
Turkey
United Kingdom
United States
1.00
0.75
0.50
0.25
0.00
2016
2018
2020
2022
Contrib. by tech.
Nuclear (clean)
Wind (clean)
Hydro (clean)
Solar (clean)
Geo. (clean)
Ren. Comb. (clean)
Oil (clean)
N. Gas (clean)
N. Gas (dirty)
Nuclear (dirty)
Wind (dirty)
Hydro (dirty)
Solar (dirty)
Geo. (clean)
Ren. Comb. (dirty)
Oil (dirty)
Coal

. (*continued*).

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