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Assessing the Evolution of the Energy Mix Worldwide, with a Focus on the Renewable Energy Transition

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Abstract. *In the current context, the focus on optimizing energy distribution is intensified by high-impact events such as resource scarcity, import dependence, war, inflation, or environmental threats. As a consequence, international agencies have built extensive policies and targets that will reflect directly into the general energy distribution. One of the most crucial would be the 65% share of electricity that is bound to be generated from renewables until 2030. To study the feasibility of that goal, we will analyze the evolution of the energy mix worldwide in the last two decades, identifying the shift towards alternative energy sources, while also pinpointing the agents of change in terms of the low-carbon transition. The methodology will consist of a bootstrap clustering algorithm that has been computed for 3 moments: 2000, 2010, and 2020, generating clear differences in terms of energy distribution. In the second part of the paper, we have employed an ARIMA model that aims to predict the share of renewable energy by 2030, with the worrying conclusion that if the current rhythm continues, the goal will not be met and the climate could face severe consequences. Therefore, the paper significantly contributes to the methodological void in terms of bootstrap clustering applicability, while also illustrating a complete energy picture from a geographical and time perspective.*

Keywords: energy mix, renewable energy, bootstrap clustering, time-series, prediction.

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Introduction

Energy production is one of the most important recurrent topics on the international agenda, especially now, in the context of high-impact events such as pandemic context, war, inflation, or resource scarcity. As a consequence, the energy mix or the distribution of energy generation and capacity will become the main framework of discussion, characterized by its significant dynamics over time and crucial importance in the climate context. In a summarized overview, this energy mix will gather three different energy aggregates: fossil fuels (which include coal, oil, and gas), nuclear energy, and renewable sources such as

hydropower, wind, solar, geothermal, or biofuels. The distribution of those will be essential for ensuring the necessary energy of a country, whether for industrial purposes, or individual, domestic ones.

However, the challenge comes from the fact that this mix has faced significant changes over time, while also maintaining a high degree of national subjectivity, based on the type of resources each country owns, the international trade relations it established, or the ultimate productive power. On another note, there are some energy trends and policies that have been dominating since the Industrial Revolution, namely the prominence of fossil fuels, the import dependence, or the relatively slow pace of transition to any new type of energy technology, whether nuclear or low-carbon. To sustain that, nowadays oil, coal, and gas still account for more than 80% energy consumption of the world (Ritchie et al., 2022), while they also generate three-quarters of the total global greenhouse gas emissions. At the same time, 80% of the global population, translated into 6 billion people, live in countries that are highly dependent on external fossil fuels, making them extremely vulnerable to any shock or crisis (IRENA, 2019). Moreover, the planet is bound to limit global warming by 2030 and achieve the net zero emissions objective by 2050, in order to increase the sustainability of the future climate, as adopted in the Paris Agreement (United Nations, 2016).

Considering all the above, the understanding of how energy sources are broken down and their variation worldwide, as well as over time, will be essential for designing the future optimal energy distribution, in a way that still ensures a high level of security, efficiency, and environmental protection. Therefore, in the current paper, we will capture three moments of the last two decades, 2000, 2010, and 2020, in order to observe if the transition towards renewable sources of energy is discernible on an international scale and has a sustainable rhythm, that can ensure the 65% renewable electricity supply goal by 2030 (IRENA, 2022). Highly correlated, the second research objective will be to look at the worldwide phenomena, with a focus on regional aggregation and similarity, while also identifying the disruptive countries or the so-called agents of change in terms of energy transition potential.

As a consequence, the first section of the paper will focus on the related literature, while also illustrating the highlighted policies and goals set up by the international agencies reports, in an endeavor to construct a profile of the current context. In the second section of the paper, we will present the dataset and the methodology behind it. In order to meet the two research objectives, we will employ a bootstrap clustering algorithm and an ARIMA time-series prediction model. The clustering technique will provide a valuable contribution to the field, since it aggregates countries with a higher degree of stability and interpretation, while also validating the optimal number of clusters. In terms of renewable energy prediction, the model will look at the historical evolution and provide insights into how the low-carbon energy trend will look in 2030. In the third and final part of the paper, we will showcase the results, along with a geographical mapping, and an interpretation of the general worldwide dynamics.

Literature review

Energy mix approaches

When studying the related literature of the field, we can see three different approaches. The first one will be a general approach, treating the energy mix subject from different perspectives such as security (Augutis et al., 2015; Thangavelu et al., 2015), the correlation

between economic growth and energy intensity (Díaz et al., 2019), (Stern, 2019), or the decarbonizing goal of switching electricity generation to intermittent sources (Ambec & Crampes, 2019). The second frequent approach is to focus on a specific case study in terms of location, and in this case, there will be a wide range of countries or regional structures that have been studied: ASEAN organization (Shi, 2016), Europe (Marrero, 2010), UAE (Said et al., 2018), being only some of the examples. Lastly, the third approach will revolve around a specific type of energy, whether in a general perspective or concentrated on a specific location. On this note, as expected, the renewable energy subject has been dominating the field recently. Some examples are profiled by Wang et al. (2018) who will discuss the role of renewable energy in the case of China's energy security, Nathaniel et al. (2020) who will link renewable energy to urbanization and ecological footprint in the Middle East and North Africa, or Vidal-Amaro et al. (2015) who will showcase the optimal transition from fossil fuels to renewable energy in the case of Mexico. At the same time, we can see a wide range of articles focused on the transition towards sustainable energy, through the lenses of materials and technologies innovation (Chu et al., 2017), or the actual integration of such strategies in socioeconomic aspects such as urbanism (Roux et al., 2016). However, besides renewable energy, we found multiple examples with a focus on nuclear energy (Brook et al., 2014) or fossil fuels (Martins et al., 2018; Kibria et al., 2019), so the field is developing at a fast pace.

Current context. International goals and targets

Next, as mentioned before, an important part of the related literature will be represented by the international institutions that provide annual reports on the current environmental and energy context, while also linking them to the necessary goals in order to limit climate threats. On this note, one essential example will be presented by the International Energy Agency, through the Renewables Report (IEA, 2022). Strongly correlated, several international policies have been designed, such as the Inflation Reduction Act (The White House, 2022), Fit for 55 (European Council, 2021), and the famous Paris Agreement (United Nations, 2016). The International Renewable Energy Agency (IRENA, 2022) and the United Nations Intergovernmental Panel on Climate Change (IPCC, 2020) can complete the list of stakeholders who are frequently contributing to the general extent of the energy status quo.

As a consequence, in an endeavor to aggregate the reports published by these institutions, we have elaborated Table 1, to showcase the current context and the targets set up and agreed upon on an international scale. This overview will be useful in the operationalization of our research objectives, to identify the global energy dynamics and the transition rhythm towards renewables.

Table 1. General environmental and energy context

Current context	**Targets**
We are on a path to surpassing 3 ° C global warming by 2030.	Limit global warming to 1.5 ° C by 2030.
Global CO2 emissions have reached the highest annual level in 2021. Fossil fuels account for more than 75% of global greenhouse gas emissions.	Global CO2 emissions must reach their peak before 2025, be cut in half by 2030, and reach net zero by 2050.

Current context	Targets
Fossil fuels account for more than 80% of global energy production, while 80% of the population lives in countries that depend on external resources. Currently, 29% of the energy comes from renewable sources. The cost of renewable energy has decreased by up to 85% in the 2010-2020 decade.	65% of the world's electricity should come from renewable sources by 2030. 90% of the world's electricity should come from renewable (cheaper) sources in 2050.

Source: Authors' own research.

Clustering methodologies review

In terms of designed methodologies and using cluster algorithms to highlight the allocation of states based on energy mix, we have identified a shortage of approaches. One example would be Saba and Ngepah (2022) who examined the convergence of 183 countries in renewable energy sources, by employing a clustering algorithm and a multinomial logit model to determine the determinants that have played a role in the renewable transition. Other models have focused on applying cluster analysis inside the European Union. This is the case for Csereklyei et al. (2017) who studied the energy paths in the European Union, in the period 1971-2010, with an illustration of major energy profiles, and also Kacperska et al. (2021) who employed a cluster analysis on the EU and Visegrad group countries.

On the other side, in regard to the prediction of renewable energy models, we have found multiple examples that study the potential of machine learning on energy prediction (Rahman et al., 2021; Lai et al., 2020; Buturache & Stancu, 2021). An integrated approach, composed of an ARIMA model, a NN, and an SVM model will be constructed by Xu et al. (2019) in order to predict with a high level of accuracy the renewable energy trend evolution worldwide, with a steady, constant growth up to 2025.

Considering all these, the current model will aim to fill in the gap in terms of bootstrap applicability on the subject, as well as depict the worldwide distribution.

Methodology

Datasets

The dataset employed in the clustering part of the model will refer to 183 countries, covering three moments: 2000, 2010, and 2020. The main indicator will be the energy mix, represented by 6 energy sources (Table 2). An important mention, in the *Fossil* variable we englobed oil, coal, and natural gas, while in the *Others* variable, we included biomass and geothermal. The initial data was calculated in billion kilowatt-hours, but the total was split to obtain the shares that together add up to 100% energy generation. The data was collected from the *U.S. Energy Information Administration*, for all the states of the world, without some exceptions for which data was unavailable either completely, or for the respective years.

Table 2. Energy mix indicators

Energy	Definition	U.m
FOSSIL	Share of total electricity generated from fossil fuels (oil, coal, and natural gas).	%
NUCLEAR	Share of total electricity generated from nuclear power.	%
WIND	Share of total electricity generated by the wind.	%
SOLAR	Share of total electricity generated by sunlight.	%

Energy	Definition	U.m
HYDRO	Share of total electricity generated from hydroelectric pumped storage.	%
OTHERS	Share of total electricity generated from alternatives (geothermal, biomass).	%

Source: Authors' own research.

In terms of evolution, in both Figure 1 and Table 3 we can see the average value for each of the six energy sources, in the period 2000-2020. We can observe that while fossil, nuclear, and hydropower are on an evident descendent trend throughout the period, wind, solar, and others are increasing from a near-null value in 2000 to values between 2-4% in 2020.

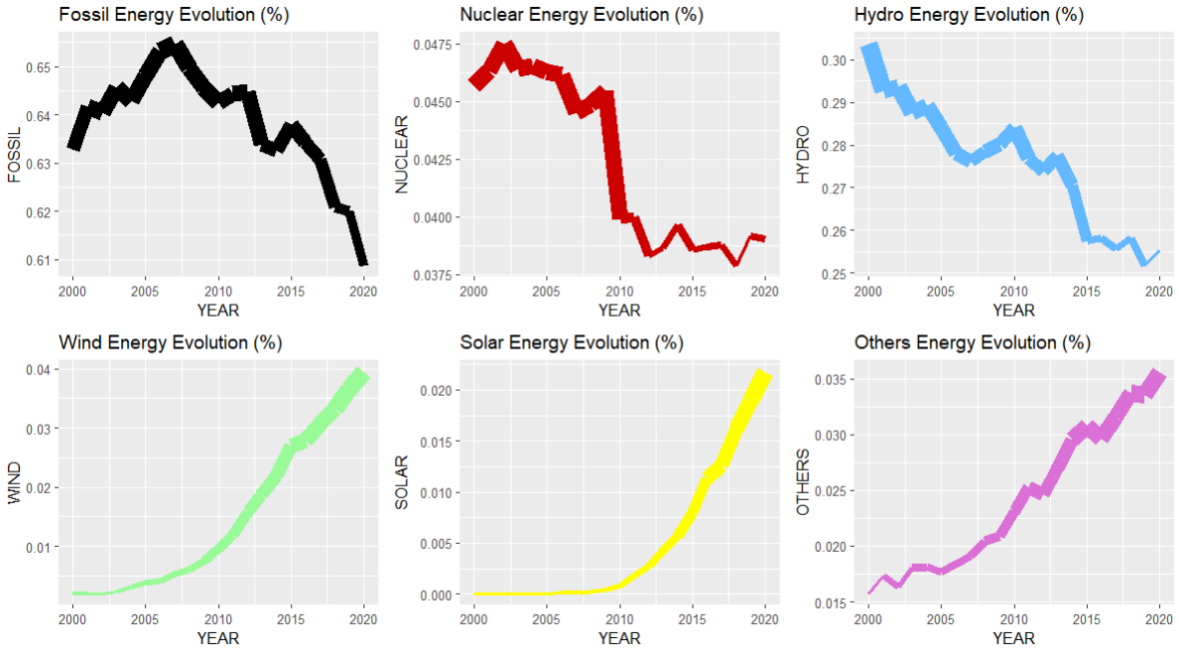


Figure 1. Evolution of worldwide energy sources, 2000-2020

Source: Authors' own research.

Further on, the standard deviation will demonstrate that there will be a wide range of diversity in terms of energy mixes, with each source varying significantly. An observation that confirms the trend mentioned previously is that for the *Wind, Solar*, and *Others* variables, the standard deviation has multiplied, meaning that there will be countries that show a big progress in terms of renewable sources adaptation, while others are stagnating.

Table 3. Descriptive Statistics, 2000-2020

Indicator	Year	Fossil	Nuclear	Wind	Solar	Hydro	Others
Mean	2000	62.1%	4.7%	0.2%	0.002%	31.3%	1.7%
	2010	62.9%	4%	0.9%	0.08%	29.6%	2.5%
	2020	60%	4%	4%	2.2%	26.4%	3.4%
Standard Dev.	2000	34.9%	13.4%	1.2%	0.01%	34.3%	4.6%

Indicator	Year	Fossil	Nuclear	Wind	Solar	Hydro	Others
Standard Dev.	2010	33.6%	11.7%	2.8%	0.3%	32.4%	5.3%
	2020	32.9%	11.5%	8.4%	3.3%	30.7%	6.9%

Source: Authors' own research.

For the prediction part of the model, the share of renewable energy has been calculated as a sum of the following energy sources: hydropower, wind, solar, and others. To obtain the average share of renewable energy worldwide, we applied a simple average. In order to increase the accuracy of prediction, the period considered was 1980-2021, with a special mention that data was not available for all countries in all the years. At the same time, the average found in Table 4 is slightly different from the ones mentioned in Table 1, since our calculation and the ones employed by the international agencies might vary in terms of the number of countries included and the general methodology.

Table 4. Descriptive Statistics, renewable energy time-series 1980-2021

Indicator	Count	Mean	Standard Dev.	Kurtosis	Skewness
REN_ENERGY	42	32%	0.3%	-1.32	-0.21

Source: Authors' own research.

Clustering Algorithm. Bootstrap evaluation

In terms of methodology, in the first stage of the analysis, we computed a hierarchical clustering algorithm. The applied method was agglomerative, and the measure used to compute the proximity matrix will be Euclidean (1). The similarity between clusters is calculated based on Ward's method (2) which minimizes the within-cluster variance at each step.

$$d_{i,j} = \sqrt{\sum_{m=1}^{p} (x_{i,m} - x_{j,m})^2} \quad (1)$$

$$W = \sum_{k=1}^{g} W_k \ where\ W_k = \sum_{i=1}^{n} \sum_{m=1}^{p} (x_{i,m} - \bar{x}_{k,m})^2 \quad (2)$$

Next, we will proceed with the hierarchical method in a bootstrap approach that aims to provide a correct cluster allocation that holds up under plausible variations, while also ensuring that overfitting is minimized. We will employ the *clusterboot()* function in the R programming language, an algorithm that uses the Jaccard coefficient, a similarity measure. Mathematically, the coefficient is described in equation (3) (Jaccard, 1901). Next, the algorithm will take a B number of bootstrap replications, compute the clustering and the maximum Jaccard coefficient, and finally generate a sequence $\gamma_{C,i}$ as a mean stability measure (4) (Hennig, 2007).

$$\gamma(C, D) = \frac{|C \cap D|}{|C \cap D|},\ C, D \subseteq x_n \quad (3)$$

$$\bar{\gamma}_C = \frac{1}{B^*} \sum_{i=1}^{B} \gamma_{C,i},\ i = 1, \dots, B \quad (4)$$

Lastly, the final decision on the optimal number of clusters is based on three criteria: the maximization of the Jaccard bootstrap means, the minimization of the number of dissolved clusters, and the maximization of the number of recovered clusters. At the same time, being a bootstrap method, there will be multiple iterations, in our case 100.

ARIMA (Autoregressive Integrated Moving Average)

ARIMA (Autoregressive Integrated Moving Average) will consist of a combination of autoregressive (AR) and moving average (MR) models, along with an integrated part that applies a differencing step to convert the time series into a stationary one. The model will be specified by three order parameters: p, the order of the autoregressive or linear model, q, the number of lagged values, and d, the difference value needed to turn the time series into a nonstationary one (5).

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p} \epsilon_t + \emptyset_1 \epsilon_{t-1} + \emptyset_2 \epsilon_{t-2} + \cdots + \emptyset_q \epsilon_{t-q} \quad (5)$$

Findings

Clustering results

As mentioned briefly before, in terms of applying the methods, we will use R Studio programming language, and more specifically, *clusterboot()* function from the *fpc* package. Through this, we will ensure the applicability of bootstrap clustering, with the algorithms being thoroughly depicted in the original source previously described, Hennig (2007), as well as (RDocumentation, n.d.).

Proceeding to the actual results section, the optimal allocation in the three periods will vary, starting from 2 clusters in 2000 and reaching 3 in 2010 and 2020. In Tables 5 to 7 we can find the clustering results, along with the distribution of states, the average share of energy resources, and the Jaccard bootstrap means. We can therefore observe that the methodology at hand had been followed, with the Jaccard coefficients being maximised in each case.

Table 5. Clusterboot optimal allocation for the 2000 year

Cluster		**Countries**	**Fossil**	**Hydro**	**Nuclear**
1	HYDRO-FOSSIL	114	42%	48%	7.4%
2	FOSSIL	68	97%	3%	0.1%
Jaccard bootstrap means: 0.86 0.82					

Source: Authors' own research.

Table 6. Clusterboot optimal allocation for the 2010 year

Cluster		**Countries**	**Fossil**	**Hydro**	**Nuclear**
1	HYDRO	50	25%	73%	0.05%
2	FOSSIL	91	91%	8%	0.2%
3	FOSSIL-HYDRO-NUCLEAR	43	48%	25%	17%
Jaccard bootstrap means: 0.90 0.94 0.81					

Source: Authors' own research.

Table 7. Clusterboot optimal allocation for the 2020 year

Cluster		Countries	Fossil	Hydro	Nuclear	Wind
1	HYDRO	39	19%	77%	0.05%	1%
2	FOSSIL	96	85%	11%	0.9%	2%
3	BALANCED	48	44%	16%	13.3%	11%
Jaccard bootstrap means: 0.93 0.86 0.78						

Source: Authors' own research.

In regards to the economic interpretation, we can see that while in 2000 the main sources of energy production were either fossil or a split between hydro and fossil, in 2010, nuclear power is gaining a share, being more prevalent in the third cluster. Moreover, in 2020, wind power and other renewable sources are increasing, a fact that contributes to the appearance of a new class named *Balanced*, gathering the states that generate energy from multiple sources (fossil, hydro, nuclear, wind, or solar). We can now link together the current context and the goals set up by the international institutions since the transition towards renewables will be more and more pre-eminent. Next, the mapping of the state allocations can be seen in Figures 2 to 4, with the methodological mention that since for some countries, we did not have the data available, the map has plotted blank spaces.

In terms of interpretation, it is worth mentioning that in 2000 the fossil-driven energy countries will be located mainly in the North and South of Africa, the Middle East, and Asia, a fact that is highly correlated with water scarcity and limited streams that can be used as an energy productive power. At the same time, it is essential to point out that this cluster will be extremely dependent on fossil resources, with an average of 97%, and a vulnerability that seems to be preserved throughout the years.

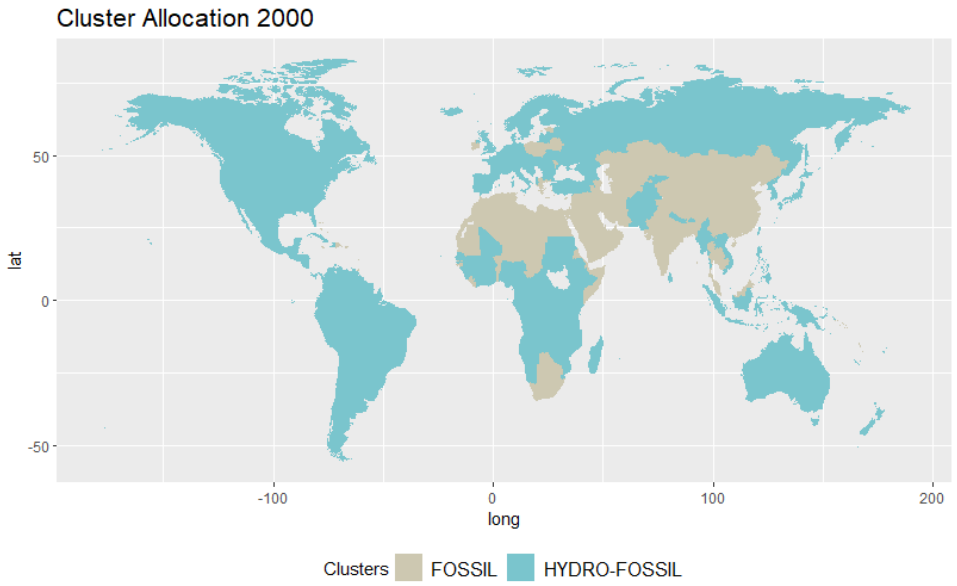


Figure 2. Cluster allocation in 2000

Source: Authors' own research.

Reaching 2010, we can see that nuclear power has gained a larger distribution and accounts for a newly created cluster named: *Fossil-Hydro-Nuclear*. This will be correlated

with the momentum that nuclear power has gained during the 2000s, a concept described as *nuclear renaissance.* During this period, a nuclear revival has been observed, boosted by the incentives and subsidies brought by the *Energy Policy Act of 2005* (IEA, 2005), as well as the high prices for fossil fuels. In terms of the representatives of this group, several regions can be considered agents of change, with North America, Russia, or Western and Central Europe being among them. However, the number of countries will remain low (23% of all included in the analysis), since both hydro and fossil-driven clusters have maintained the majority. In terms of global distribution, we can distinguish the fossil-driven countries being prevalent in Northern Africa, the Middle East, or Asia (similar to 2000), while the hydro-driven ones will be observed throughout the North region of South America, the Central and South parts of Africa, Indochina, and Northern Europe.

Finally, in 2020 we can see the formation of a new cluster, named Balanced, showing the regions that rely on a multitude of energy sources, including modern renewables. In this category, we can see the United States, Chile, Australia, Russia, and Western and Central Europe. At the same time, the hydro-driven category remains similar to the 2010 distribution (losing a number of 10 countries), while the number of fossil-driven states has slightly increased versus 2010 due to resource scarcity and increasing fossil fuel import dependencies.

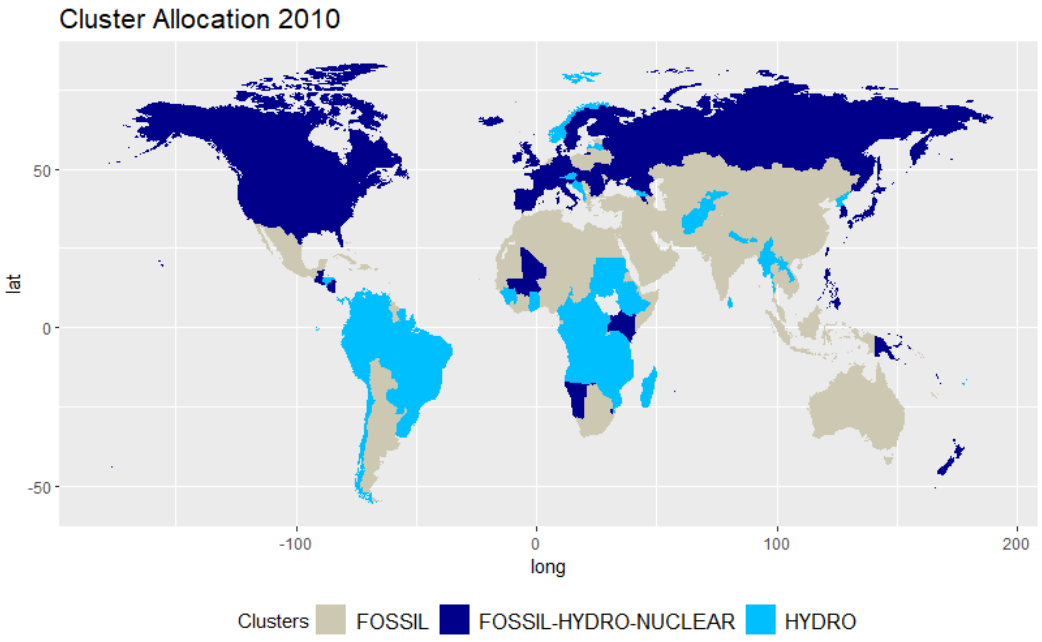


Figure 3. Cluster allocation in 2010

Source: Authors' own research.

Unfortunately, the high dependence on fossil fuels has left the world with a never-seen-before vulnerability, which has transitioned into what we already know as the energy crisis of 2021-2022. Several factors have played a role, including the depletion of owned resources, the COVID-19 pandemic, and the armed conflicts that have impacted and still impact the European continent.

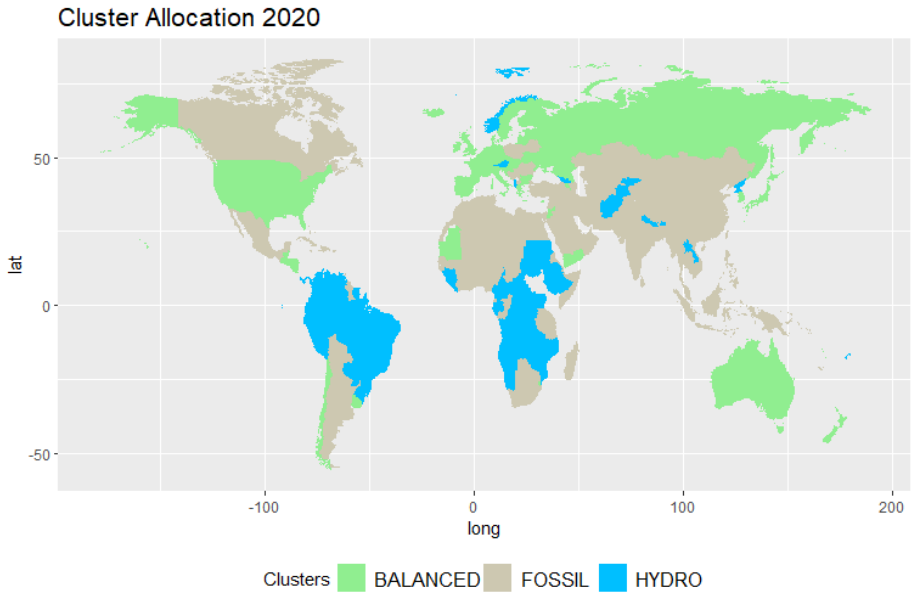


Figure 4. Cluster allocation in 2020

Source: Authors' own research.

Lastly, we can consider that the first objective of our paper, namely to illustrate the regional dynamics and evolution over time, has been achieved, with a clear trend of transitioning to a mix of energy sources, including renewables. At the same time, the agents of change have been illustrated, as being synonymous with the countries that are included in the *Balanced* cluster. However, in order to assess if the current transition rhythm can help reach the 65% goal, we need to apply the ARIMA model and predict the share by 2030, based on historical data.

ARIMA model results. Predicting the share of renewable energy by 2030

Therefore, in the second part of the model, we have used a time-series dataset, for which we first studied stationarity, through the use of the *Augmented Dickey-Fuller* test. This instrument helps identify whether a series is stationary or not, or if the characteristics of the data depend on time. After applying it, we have accepted the null hypothesis and concluded that the time series is non-stationary, so the generative process behind this series does change over time. Therefore, we can now apply the ARIMA model, as described in the methodological part, using the *auto.arima()* function and the *forecast* package (RDocumentation, n.d.). This method has been designed to return the best ARIMA model according to the *AICc (Corrected Akaike Information Criterion*), an indicator that evaluates the goodness of fit in a time-series model. The statistics can be seen in Table 8.

Table 8. auto.arima() output in R Studio

ARIMA (0,2,2)		
Coefficients	**ma1**	**ma2**
	-1.182	0.33
s.e	0.189	0.184
$sigma^2 = 0.4473$	Log likelihood = -40.53	
AIC = 87.1	AICc = 87.7	BIC = 91.13

Source: Authors' own research.

After identifying the optimal result as the ARIMA (0,2,2), a model that predicts that the second difference of the series equals a linear function of the last two forecast errors, we can now proceed to illustrate the predicted values (Table 9), as well as the graphical representation (Figure 5).

Table 9. Average Share of Renewable Energy – 2030

Forecast		Lo 95	Hi 95
2022	37.4%	36.1%	38.7%
2023	37.9%	36.3%	39.6%
2024	38.5%	36.4%	40.6%
2025	39%	36.5%	41.6%
2026	39.6%	36.5%	42.6%
2027	40.1%	36.6%	43.7%
2028	40.7%	36.6%	44.8%
2029	41.2%	36.5%	45.9%
2030	41.8%	36.5%	47.0%

Source: Authors' own research.

In terms of interpretation, we can see that if the current trend continues, in 2030 around 42% of the world's energy generation will come from renewable sources, a constant but slow growth of around 8% in a decade. This value is worrying since to reach the share of climate milestones, renewable energy needs to increase to a level of 65% by 2030. However, 2022 was a year of record-breaking investments in terms of renewable energy capacity, a fact that corroborated with the main key policies and scenarios agreed upon on the international stage, can push progress to a new rhythm that can exceed the level predicted in the *high 95%* confidence interval (47% by 2030).

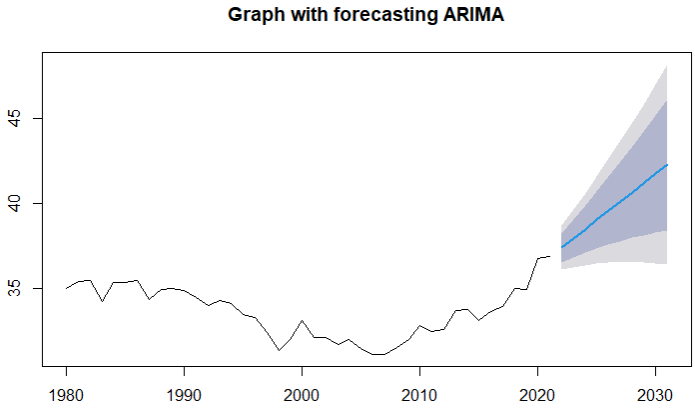


Figure 5. Forecasted level of renewable energy, until 2030

Source: Authors' own research.

Conclusion

In summary, the optimization of the energy mix remains an international priority, with a focus on the transition to renewable resources. By analysing the evolution in the last two decades using bootstrap clustering, we could observe the switch from fossil fuel resources to nuclear energy in 2010, and then to a balanced combination of energy technologies in 2020. The Balanced cluster countries could be perceived as agents of change since the low-carbon

energy resources help to drastically reduce greenhouse gas emissions and limit the global warming level. The United States, Europe, and Russia are definitely leading the race towards renewable energy, a consequence of both the availability of natural resources and a robust national strategy. However, the number of states that still rely mainly on fossil remains extremely high, a fact that needs to become a priority in order to increase shock's resilience.

Secondly, by computing the ARIMA model, we have predicted the renewable energy share by 2030, reaching an optimistic 47% share value. However, compared to the objective of 65%, the conclusion could be that if the following transition rhythm continues, the target will no longer be reachable, a fact that could have severe consequences for the climate and humanity. In this context, international policies and action plans are playing an immense role, whether they are legally binding, or just designed as a support system, providing the necessary frameworks for initiating, adjusting, and enhancing the renewable transition, with hopefully incremental results year on year.

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