

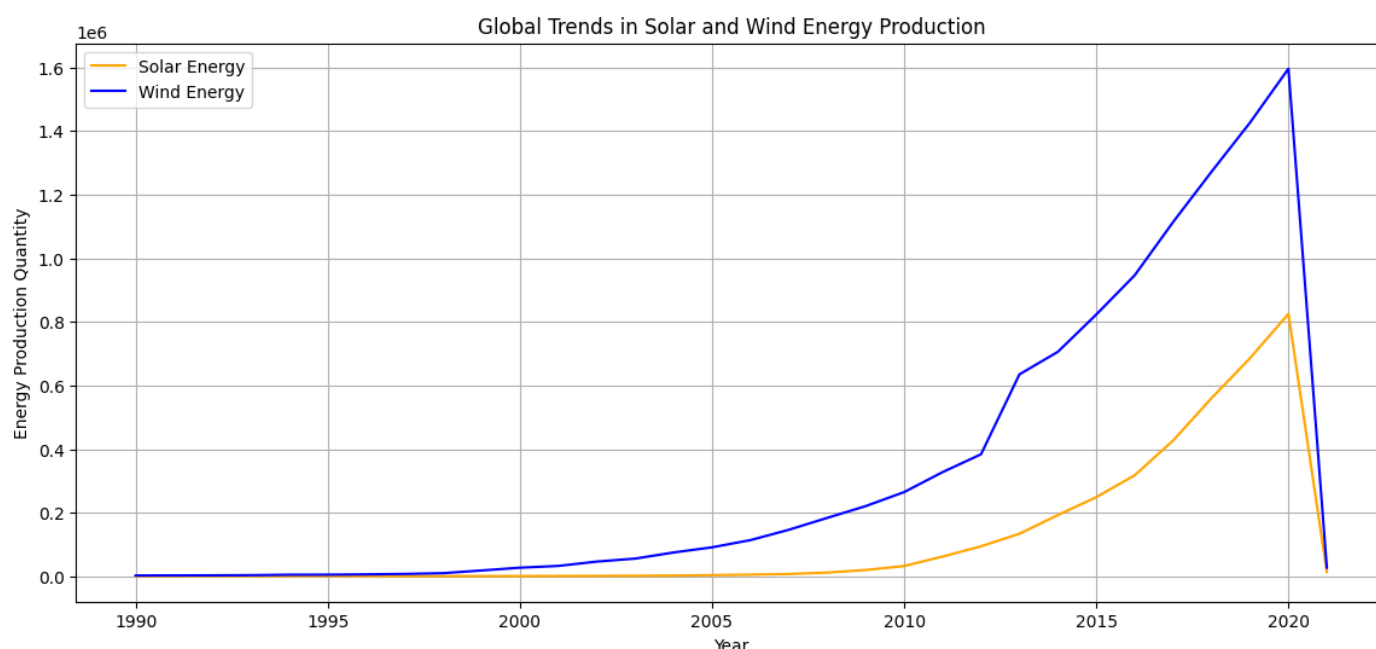
## 1. Introduction

The UNSD Energy Statistics Database provides detailed information on energy production and consumption since 1990. These data are crucial for developing blockchain-based technical assistance projects by Blockchain Climate Institute (BCI), which collaborates with governments and stakeholders in the energy sector.

The energy statistics are vital for energy generation and distribution companies, as well as for large real estate managers, helping them to understand changes in the energy sector and identify opportunities to maximize revenues and positive environmental impacts.

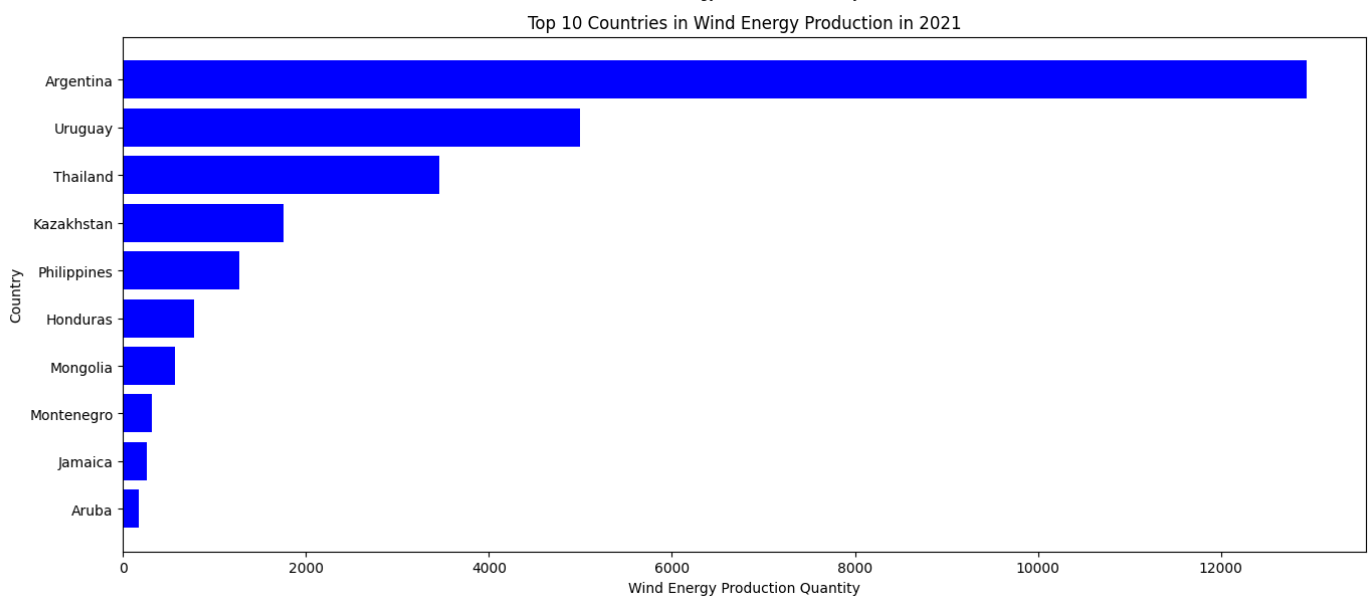
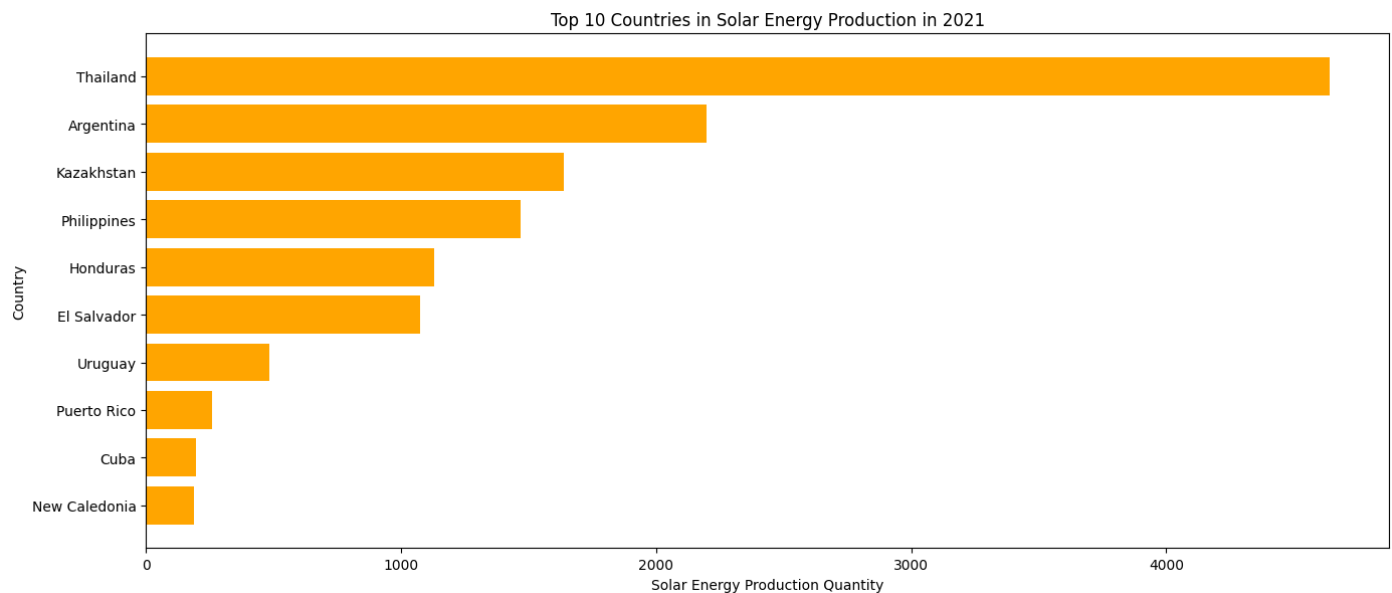
## 2. Global Trends in Renewable Energy:

- **Solar Energy:** A marked global increase in solar energy production is evident, showcasing a robust adoption curve.
- **Wind Energy:** There's also a significant global uptrend in wind energy production, with some yearly variability but a clear positive trajectory overall.



## 3. Leaders in Renewable Energy for 2021:

- **Solar:** Thailand, Argentina, and Kazakhstan lead in solar energy production, with Thailand at the forefront by a substantial margin.
- **Wind:** Argentina tops wind energy production, followed by Uruguay and Thailand. Argentina's production is notably higher than other leading countries.



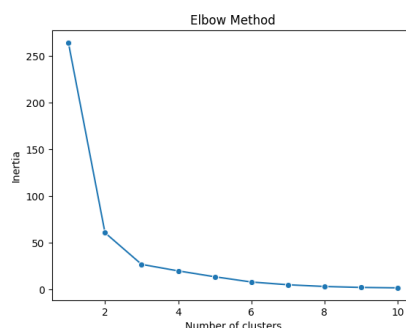
#### 4. Aggressive Adoption:

- Solar: Honduras, El Salvador, and Uruguay show remarkable figures given their economies' size, indicating aggressive adoption relative to their capacities.
- Wind: Argentina and Uruguay stand out, suggesting focused national energy policies or favorable investment climates for wind energy.

#### 5. Renewable Energy Clustering Approach:

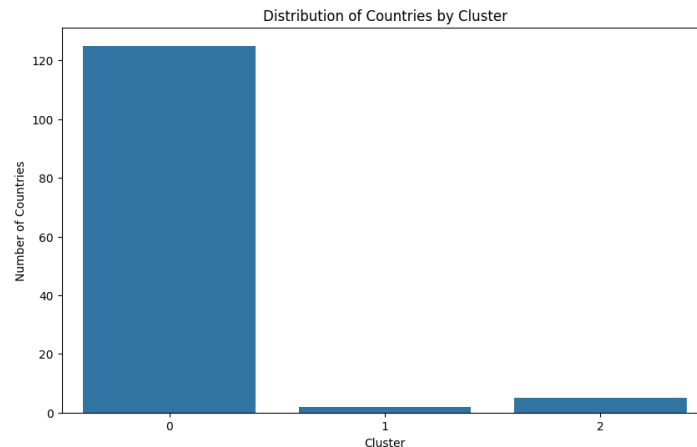
##### a. Analysis of the Elbow Method Graph:

- The Elbow Method graph suggests that after three clusters, the decrease in inertia becomes marginal, indicating that three clusters are a good balance between complexity and explaining variance within the data.
- This implies that the global energy market can be roughly divided into three distinct groups based on the adoption and production of wind and solar energy.



b. Analysis of Cluster Distribution:

- The majority of countries fall into a single cluster (Cluster 0), suggesting that most have a similar energy profile regarding wind and solar energy production.
- There are significantly fewer countries in Clusters 1 and 2, indicating that these clusters represent countries with more distinctive energy production profiles in terms of wind and solar energy.



c. Inspection of Clustered Countries:

- Cluster 0 may include countries with generally lower overall production of wind and solar energy.
- Cluster 1 includes countries like China and the United States, which are likely to be high producers of wind and solar energy.
- Cluster 2 contains countries such as Germany, India, Italy, Japan, and Spain, known for substantial renewable energy production but may have different energy mixes or adoption rates compared to Cluster 1.

d. Implications for Renewable Energy Strategy:

- Countries in Cluster 0 may represent potential targets for increased technical assistance and investment in renewable energy infrastructure.
- Clusters 1 and 2 may consist of countries that could serve as models for renewable energy adoption or could be in a position to export technology and expertise.

e. Strategic Development:

- The BCI could use these insights to tailor their blockchain-based technical assistance projects, focusing on different strategies for each cluster group.
- For countries in Cluster 0, the focus could be on initiating renewable energy adoption, whereas for countries in Clusters 1 and 2, the focus could be on optimization and technological advancement.

This clustering approach provides a nuanced understanding of the global renewable energy landscape, which is vital for strategic planning and decision-making within the BCI and for advising partner countries on sustainable energy projects.

## 6. Substantial Changes in Categories:

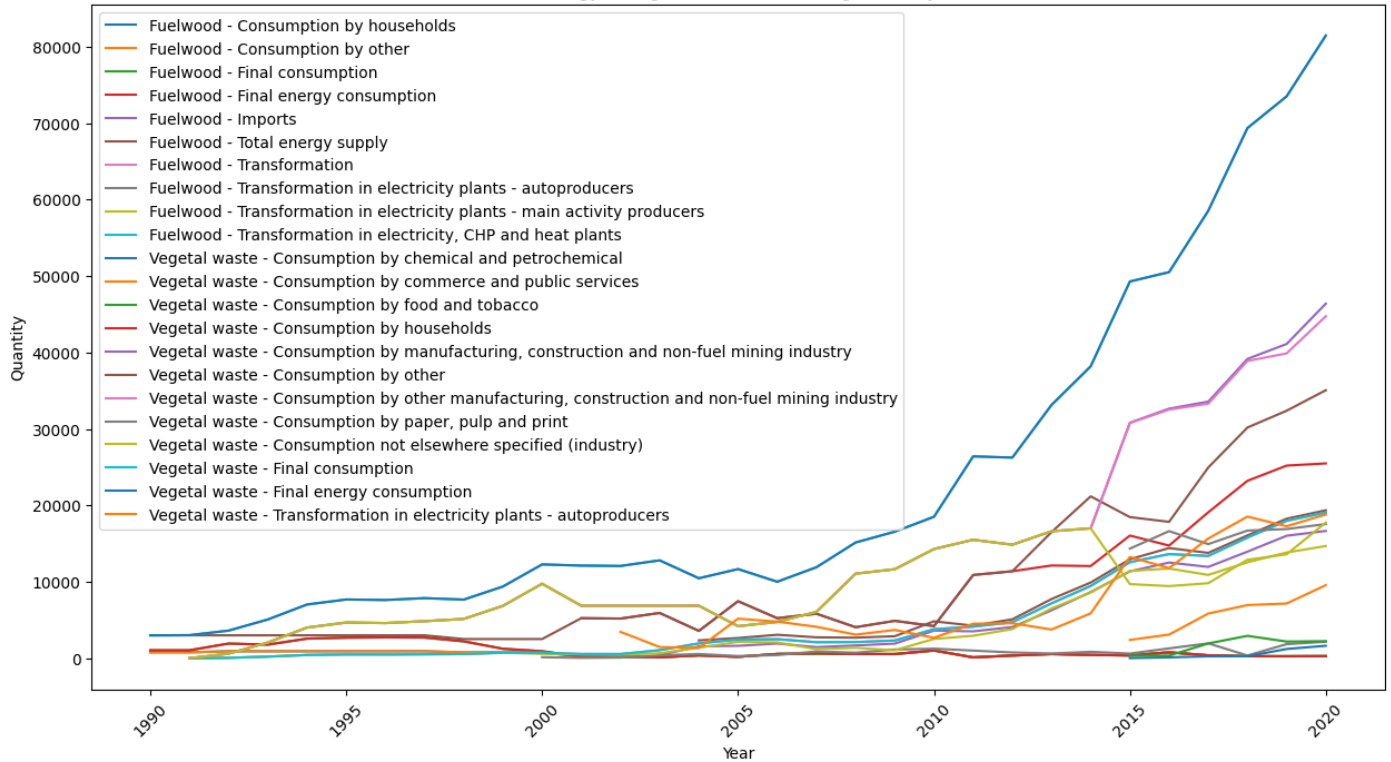
The most notable trend is a significant increase in a category that seems to be related to "Fuelwood - Transformation in electricity plants - autoproducers." There is a sharp upward trajectory starting around 2010, suggesting a substantial increase in the use of fuelwood for electricity generation by autoproducers in the UK.

Another category that shows a clear increase, though not as steep, appears to be "Vegetal waste - Transformation in electricity plants - autoproducers." This indicates that vegetal waste is increasingly being used for electricity generation, aligning with the trend of using biofuels as a renewable energy source.

Several categories related to vegetal waste consumption by different sectors (like chemicals, petrochemicals, commerce, public services, and households) are also showing an upward trend, although they begin to increase at different points in time, indicating a growing utilization of vegetal waste as a source of energy across various industries.

These observed trends suggest a focus on renewable energy sources and a shift towards more sustainable energy practices within the UK, particularly in the last decade. The use of biofuels, such as fuelwood and vegetal waste, in electricity generation has notably increased, reflecting a possible policy shift towards green energy and sustainability.

Trends in Energy Categories with Increasing Quantity in the UK



## 7. Analysis of Energy Flow Patterns for Relevant Stakeholders

### a. Energy Generation & Distribution Companies:

- Focus on Production Flows (CL01): Identifying trends in energy production, such as increases or decreases in generation from specific sources, is crucial for these companies.
- Imports and Exports (CL03 and CL04): Analyzing the balance between energy imports and exports can indicate external dependencies or market opportunities.
- Energy Transformation (CL08, CL08811, CL08812): Observing how energy is transformed, especially in electricity plants and CHP plants, can reveal efficiencies or inefficiencies in the energy generation process.
- Own Use by Energy Industries (CL09): Understanding the amount of energy consumed internally by energy industries can highlight areas for improvements in energy efficiency.

### b. Large Real Estate Managers/Owners:

- Final Consumption (CLNA, CL12): Analyzing energy consumption across different sectors, especially in commercial and residential buildings (CL1231, CL1235), is critical to understanding energy demands and potential savings.
- Non-energy Uses (CL11): Understanding energy used for non-energy purposes, such as raw materials in industrial processes, can help identify efficiency opportunities.
- Losses (CL101): Identifying where the most significant energy losses occur in the distribution process can help optimize energy use in buildings and facilities.

### c. Relevant Patterns:

- Trends in Renewability and Sustainability: Shifts in energy production and consumption patterns towards more sustainable sources are vital for both organizations, in line with the increasing emphasis on sustainability.
- Opportunities for Technological Innovation: Identifying patterns in energy flows can reveal opportunities for introducing new technologies, such as blockchain-based systems to improve efficiency, transparency, and security in energy management.

### 8. Question 3

I do not have a particular preference for any specific analytical method. That said, I understand that the best method or approach is the one that yields the best result. Thus, we can discuss the following methods and approaches when it comes to forecasting time series. (It is worth noting that in the notebook, I applied the ARIMA method and, considering the short time frame, it produced a very good result)

a. ARIMA (Autoregressive Integrated Moving Average):

- Why: ARIMA is a popular and widely used statistical method for time-series forecasting that can capture trends, seasonality, and cycles in historical data.
- Use Case: Ideal for datasets with a clear trend or seasonal patterns, which is often the case with energy production data.
- Region/Energy Variation: Parameters of the ARIMA model ( $p$ ,  $d$ ,  $q$ ) would be tuned specifically for each dataset. For instance, wind energy data might have different seasonality factors in the UK compared to a global dataset.

b. SARIMA (Seasonal ARIMA):

- Why: Includes seasonal terms to account for seasonality in data, which can be a significant factor in energy production due to weather patterns.
- Use Case: Best for regions where energy production has strong seasonal behavior, like solar energy in regions with distinct sunny and cloudy seasons.

c. Prophet:

- Why: Developed by Facebook, it's robust to missing data and shifts in the trend, and it can handle outliers well.
- Use Case: Useful when the data has irregular trends or when incorporating holidays and events that could affect energy consumption or production.

d. Machine Learning Models (Random Forest, Gradient Boosting Machines):

- Why: Can capture complex nonlinear relationships in the data. They are particularly useful when there are multiple influencing factors on energy production.
- Use Case: When there are additional data features available (e.g., economic indicators, policy changes) that could influence forecasts.

e. Deep Learning (RNN, LSTM):

- Why: These models can learn from sequences of data, making them suitable for time-series forecasting where past information is used to predict future trends.
- Use Case: When dealing with very large datasets or when fine-grained temporal resolutions (hourly, daily) are involved.

f. Hybrid Models:

- Why: Combining different models can leverage the strengths of each to improve forecast accuracy.
- Use Case: When a single model doesn't provide adequate forecast accuracy, a combination of models can be used to enhance predictions.

Different regions and energy types might require different models due to varying external factors such as policy changes, economic conditions, technological advancements, and natural resource availability. For instance, forecasting wind energy in a coastal region may require models that can account for more volatile weather conditions compared to a more stable inland region. Similarly, solar energy predictions might need to factor in more seasonality compared to wind energy.

Overall, the choice of forecasting technique would be data-driven, based on the historical data patterns, the external factors influencing the energy production, and the specific forecasting goals. Model selection would involve

exploratory data analysis and experimentation with different models to evaluate which provides the most accurate and reliable forecasts.

#### 9. Question 4

##### a. Potential Issues with the Dataset:

- **Data Quality:** Depending on the sources and methods of data collection, there might be issues of accuracy and consistency within the dataset. Inconsistencies in measurement units, gaps in data for certain years or countries, and potential errors in data entry are common challenges that could affect the reliability of the analysis.
- **Bias:** There might be inherent biases in the data due to the overrepresentation or underrepresentation of certain regions or types of energy. For instance, if certain countries have more comprehensive data collection methods for renewable energy, the dataset may skew towards those countries' energy profiles.
- **Completeness:** Missing data for certain years or countries can lead to incomplete analysis, particularly when forecasting future trends. It's crucial to ensure that the data spans a comprehensive timeline and covers a broad geographic scope to avoid skewed insights.

##### b. Interesting Findings

- **Trends in Renewable Energy:** The dataset might reveal significant upward trends in the production and consumption of renewable energy, which could inform stakeholders about the shifting energy landscape and the potential for investment in renewable technologies.
- **Regional Differences:** The analysis may uncover regional differences in energy production and consumption, providing insights into how different areas might require tailored energy policies or infrastructure investments.
- **Impact of Policies:** The dataset could show the impact of policy changes or international agreements on energy production trends, particularly for renewables, indicating how regulatory environments shape the energy sector.
- **Technological Advancements:** Trends might reflect the impact of technological advancements on increasing energy efficiency or enabling new forms of energy production, which could be of interest to tech companies and investors.

These findings from the dataset can offer valuable insights to various stakeholders described in the problem description, such as governments prioritizing energy, energy generation and distribution companies, and large real estate managers or owners. The insights can aid in strategic planning, policymaking, investment decisions, and the development of blockchain-based technical assistance projects.

Link: [https://github.com/willianpina/Freelancer Productions/tree/main/Energy%20Market%20Data%20Analysis](https://github.com/willianpina/Freelancer_Productions/tree/main/Energy%20Market%20Data%20Analysis)