

# Project Report

## **The Relationship Between Renewable Energy Consumption and GDP Growth in the United Kingdom**

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## **1. Problem Definition**

This study focuses on a comprehensive analysis of the relationship between renewable and waste-based energy components and economic growth. The research examines not only the relationship between total energy consumption and Gross Domestic Product (GDP) growth, but also the extent to which renewable energy sub-components such as hydroelectric, wind-wave-tidal, solar, geothermal, landfill gas, sewage gas, biomass, municipal solid waste, poultry litter, straw, wood, charcoal, liquid bio-fuels, bioethanol, biodiesel, biomass and cross-boundary adjustment are related to economic growth. The importance of this topic stems from the fact that, despite the accelerating global energy transition process, the literature lacks a definitive and uniform conclusion regarding the impact of renewable energy use on economic growth. Determining whether renewable energy investments stimulate economic growth, and which energy types show stronger or weaker relationships with economic growth, is critical for designing energy policies, creating incentive mechanisms, and developing sustainable development strategies. Furthermore, the observation of negative correlations between some renewable energy components and economic growth suggests that this relationship may be complex and non-linear, necessitating a detailed empirical investigation of the subject.

## **2. Literature Review**

The relationship between renewable energy consumption and economic growth has become an increasingly studied topic in the literature, especially with the rise of climate change mitigation and sustainable development goals. Strong theoretical arguments exist suggesting that renewable energy can support economic growth through capital accumulation, increased employment, technological innovation, and reduced dependence on energy imports. However, the results of empirical studies are not entirely uniform, and the direction and magnitude of the relationship vary depending on the country, the time period, and the methodology used.

Current literature examines the causal dynamics between renewable energy consumption and economic growth using various methods. A study by Atchuthen and Kumar analyzed the interaction between renewable energy consumption, carbon emissions, and economic growth, demonstrating that renewable energy can have a statistically significant and positive effect on economic growth in the long term. These findings support the "growth hypothesis," which suggests that increases in renewable energy capacity stimulate capital formation and technological progress (Atchuthen & Kumar, 2023). Similarly, an empirical analysis by Dias found a positive relationship between renewable energy consumption and GDP growth, but showed that the intensity of this effect can vary depending on factors such as the structure of energy markets and the level of technological maturity (Dias, 2022).

Conversely, some studies emphasize that the relationship in question may have a time-dependent and non-linear structure. In the study conducted by Hung, the effects of macroeconomic uncertainties and structural breaks on the energy-growth relationship were examined; it was concluded that the direction of causality can differ across periods (Hung, 2025). These findings show that crises, policy changes, and energy price shocks can transform the structure of the relationship, and that fixed-coefficient linear models may not be sufficient in all cases.

The COVID-19 period represents a significant turning point in evaluating the relationship between renewable energy and economic growth. Literature on the pandemic reveals that while short-term economic contraction and fluctuations in energy demand became more pronounced, recovery packages and green investment policies strengthened long-term expectations for renewable energy (Magazzino, Mele, & Morelli, 2021). In this context, the pandemic reshaped the position of renewable energy investments within economic recovery strategies and increased the importance of green transformation policies.

While the current literature makes significant contributions, it also contains certain gaps. First, many studies treat renewable energy consumption as a total variable; studies that examine energy types such as solar, wind, hydroelectric, and biomass in detail are limited. Second, a significant portion of the research relies on traditional econometric models, and methods capable of capturing nonlinear relationships are less frequently used. Third, while studies on multi-country panels are common, detailed examinations focusing on a single country require more research, especially for countries with significant energy transition processes.

In this context, the present study aims to contribute to the literature in three main ways. Firstly, renewable and waste-based energy components are separated and their relationships with economic growth are examined separately. Secondly, machine learning-based models such as Random Forest and Gradient Boosting are used to reveal nonlinear interactions and variable significance. Thirdly, structural breaks are reflected in the model by applying time-based data separation, and periodic dynamics are taken into account.

Overall, the literature shows that the relationship between renewable energy consumption and economic growth is complex, context-sensitive, and largely dependent on the methodology used. While most studies point to a positive relationship, some periods have yielded weak or statistically insignificant results. This suggests that linear econometric models with fixed coefficients may be insufficient to explain the entire structure of the energy-growth relationship.

In this context, machine learning-based ensemble methods, which can capture nonlinear relationships and complex interactions between variables, are increasingly used in the literature. The Random Forest model developed by Breiman (2001) provides robust and overfitting-resistant estimates by combining numerous decision trees through bootstrap sampling and random variable selection. Furthermore, its ability to calculate variable significance levels allows for the analysis of the relative effects of energy components on economic growth.

Due to these methodological advantages, the Random Forest approach is considered a suitable tool for analyzing the renewable energy-economic growth relationship, whose effects can vary over time and depending on the type of energy. This study adopts a machine learning-based approach that complements the existing econometric literature.

### **3. Methodology**

#### **3.1. Identification and Integration of Datasets**

This research used two datasets to examine the relationship between renewable energy consumption and economic growth in the United Kingdom. The first is the UK Renewable Energy Consumption Dataset, compiled by magnussesodia on the Kaggle platform, which includes annual consumption figures for hydroelectric, wind-wave-tidal, solar, geothermal,

landfill gas, sewage gas, biomass, municipal solid waste, poultry manure, straw, wood, coal, liquid biofuels, bioethanol, biodiesel, and cross-border adjustment. The second is the GDP Growth (Annual %) dataset, published by the World Bank, which includes annual GDP growth rates for the UK economy. The study used observations from both datasets covering the period 1990–2020; the datasets were matched and integrated on a year-by-year basis. This created an integrated dataset covering the 30-year period, and the analyses were performed based on this dataset.

### 3.2. Data Preprocessing

In this study, the dataset on renewable energy consumption and the dataset containing GDP growth rates were combined in Excel, variable names were harmonized, and a single integrated dataset was obtained. Thus, the final data structure to be used in the modeling and analysis phases was created.

**Figure 1.** Renaming variable names.

Energy from renewable & waste sources	→ renew_waste_energy
Total energy consumption of primary fuels	→ total_energy
Fraction from renewable sources and waste	→ renew_waste_share
Hydroelectric power	→ hydro
Wind, wave, tidal	→ wind_wave_tidal
Solar photovoltaic	→ solar
Geothermal aquifers	→ geothermal
Landfill gas	→ landfill_gas
Sewage gas	→ sewage_gas
Biogas from autogen	→ biogas
Municipal solid waste (MSW)	→ municipal_waste
Poultry litter	→ poultry_litter
Straw	→ straw
Wood	→ wood
Charcoal	→ charcoal
Liquid bio-fuels	→ liquid_biofuels
Bioethanol	→ bioethanol
Biodiesel	→ biodiesel
Biomass	→ biomass
Cross-boundary Adjustment	→ cross_border

The datasets were imported into the Python environment; the number of observations, variable types, and possible missing observations were examined in detail using the head, tail, and info functions. Accordingly, data consistency was checked, the variables to be used in the analysis were determined, and the structural characteristics of the dataset were evaluated using descriptive statistics. As a result of these processes, it was confirmed that the dataset was suitable for empirical analysis and modeling stages.

**Figure 2.** df.head()

	year	renew_waste_energy	total_energy	renew_waste_share	hydro	wind_wave_tidal	solar	geothermal	landfill_gas	sewage_gas	...
0	1990	1.647	225.532	0.007	0.448	0.001	0.0	0.001	0.080	0.138	...
1	1991	1.634	231.288	0.007	0.398	0.001	0.0	0.001	0.105	0.151	...
2	1992	1.843	228.696	0.008	0.467	0.003	0.0	0.001	0.155	0.151	...
3	1993	1.862	231.368	0.008	0.370	0.019	0.0	0.001	0.162	0.158	...
4	1994	2.528	230.739	0.011	0.438	0.030	0.0	0.001	0.188	0.170	...

5 rows × 22 columns

**Figure 3.** df.tail()

	year	renew_waste_energy	total_energy	renew_waste_share	hydro	wind_wave_tidal	solar	geothermal	landfill_gas	sewage_gas	
26	2016	16.750	202.261	0.083	0.46		3.195	0.894	0.001	1.556	0.387
27	2017	18.656	197.273	0.095	0.51		4.268	0.985	0.001	1.419	0.398
28	2018	21.034	198.125	0.106	0.47		4.893	1.089	0.001	1.298	0.407
29	2019	22.871	192.500	0.119	0.50		5.485	1.082	0.001	1.202	0.434
30	2020	24.472	169.439	0.144	0.58		6.481	1.131	0.001	1.160	0.440

5 rows × 22 columns

**Figure 4.** df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 31 entries, 0 to 30
Data columns (total 22 columns):
 #   Column           Non-Null Count  Dtype  
--- 
 0   year            31 non-null      int64  
 1   renew_waste_energy 31 non-null    float64 
 2   total_energy      31 non-null    float64 
 3   renew_waste_share 31 non-null    float64 
 4   hydro             31 non-null    float64 
 5   wind_wave_tidal   31 non-null    float64 
 6   solar             31 non-null    float64 
 7   geothermal         31 non-null    float64 
 8   landfill_gas      31 non-null    float64 
 9   sewage_gas         31 non-null    float64 
 10  biogas            31 non-null    float64 
 11  municipal_waste   31 non-null    float64 
 12  poultry_litter    31 non-null    float64 
 13  straw              31 non-null    float64 
 14  wood               31 non-null    float64 
 15  charcoal           31 non-null    float64 
 16  liquid_biofuels   31 non-null    float64 
 17  bioethanol          31 non-null    float64 
 18  biodiesel           31 non-null    float64 
 19  biomass             31 non-null    float64 
 20  cross_border        31 non-null    float64 
 21  GDP_growth          31 non-null    float64 
dtypes: float64(21), int64(1)
memory usage: 5.5 KB
```

### 3.3 Exploratory Data Analysis

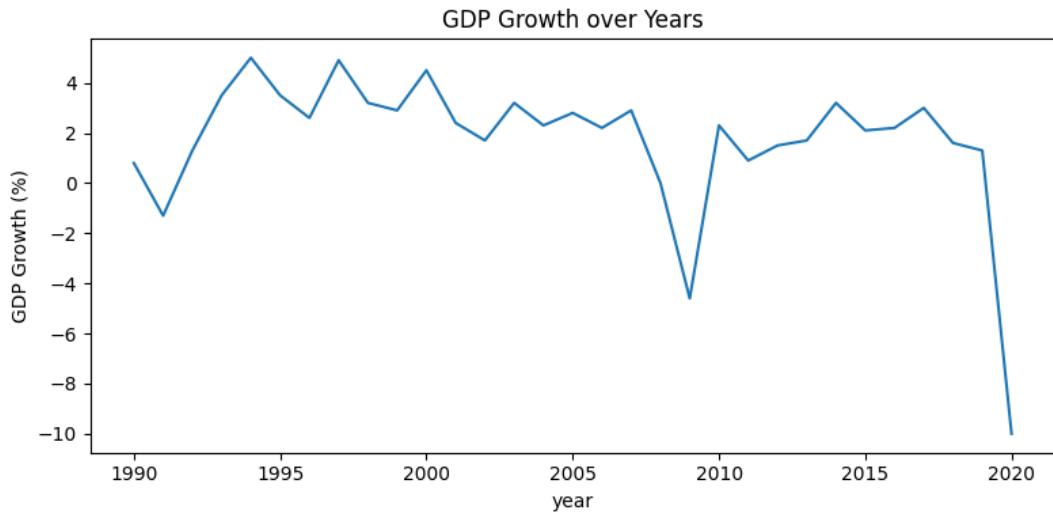
This section examines key trends and visual patterns related to economic growth and renewable energy indicators. The behavior of the variables used in the study over time, their degree of co-occurrence, and the differences between components are evaluated through graphs. Within the scope of exploratory data analysis, the year-on-year variation in GDP growth rate, trends in renewable and waste-based energy consumption, the co-occurrence of economic growth and energy consumption, and the composition of renewable energy sub-components over time are analyzed in detail. These analyses provide preliminary information for the correlation and modeling analyses to be conducted in subsequent sections and contribute to a better understanding of the dataset's structure.

#### 3.3.1 Analysis of the Economic Growth Trend

The trajectory of the GDP growth rate over the years is visualized with a time series graph. In Figure 5, significant fluctuations in growth rates, periods of economic crisis, and recovery processes can be clearly observed. The graph reveals that economic growth does not exhibit a

stable structure; it shows a volatile character sensitive to external shocks. This indicates that the relationship between energy demand and growth may change periodically.

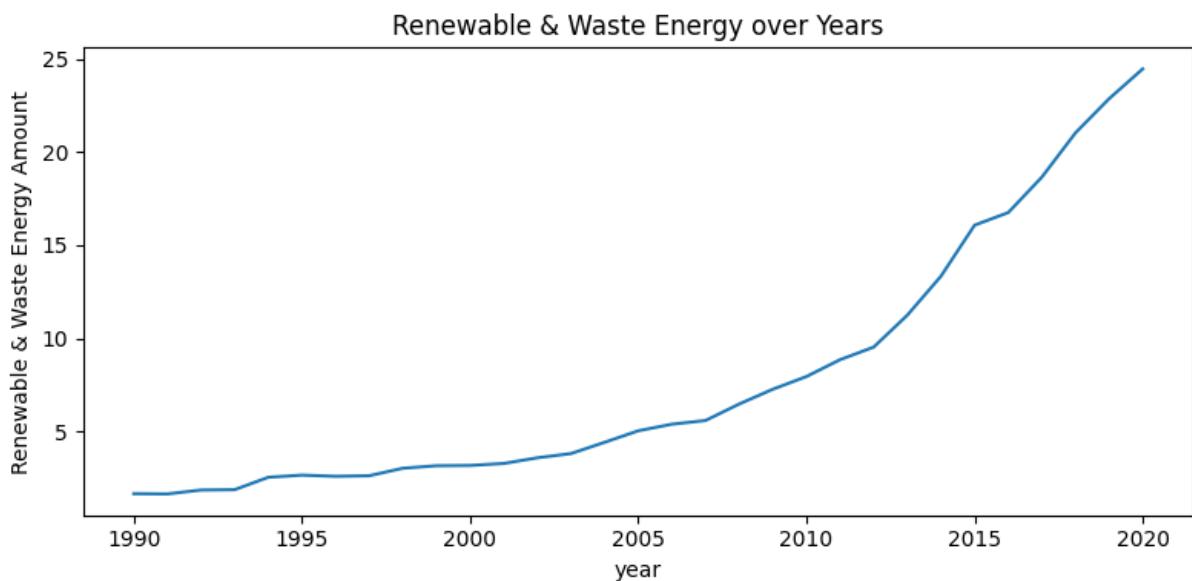
**Figure 5.** GDP growth over years



### 3.3.2 Analysis of Renewable and Waste-Based Energy Consumption Trends

The development of renewable and waste-based energy consumption over the years is presented in a time series graph. Figure 6 shows a generally increasing trend, although there are temporary declines and plateaus in some periods. This finding indicates that the energy transition process is not linear and uninterrupted, but is affected by policy changes and economic conditions.

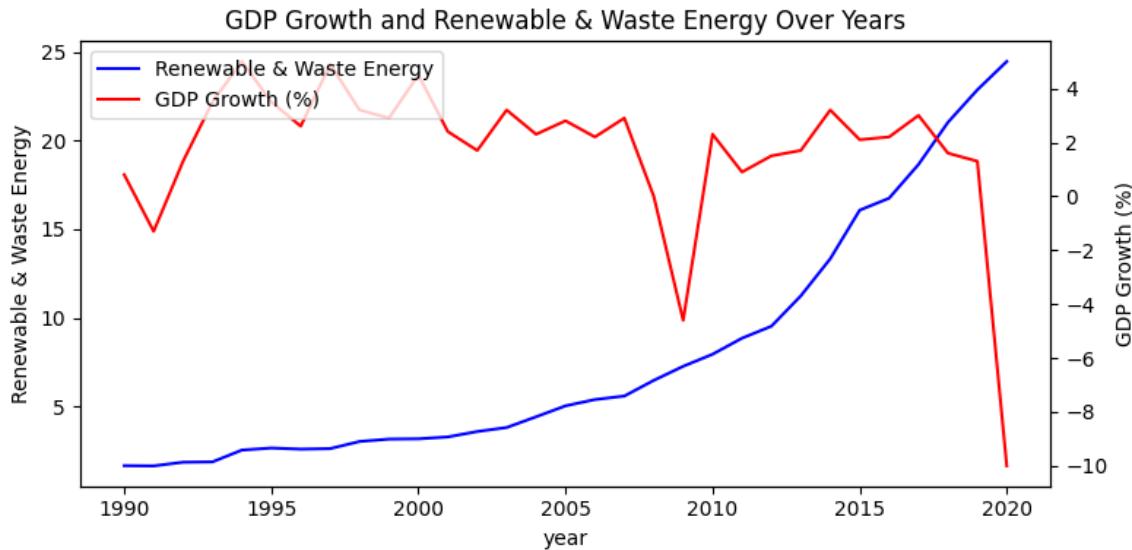
**Figure 6.** Renewable & Waste Energy over years



### 3.3.3 Investigating the Nexus Between Economic Growth and Energy Consumption

GDP growth rate and renewable energy consumption were evaluated together and presented in a two-axis graph. Figure 7 shows that the tendency for the two variables to move together strengthens in some periods, while divergences occur in other periods. This indicates that the relationship is not fixed and unidirectional; it varies depending on the periodic conditions.

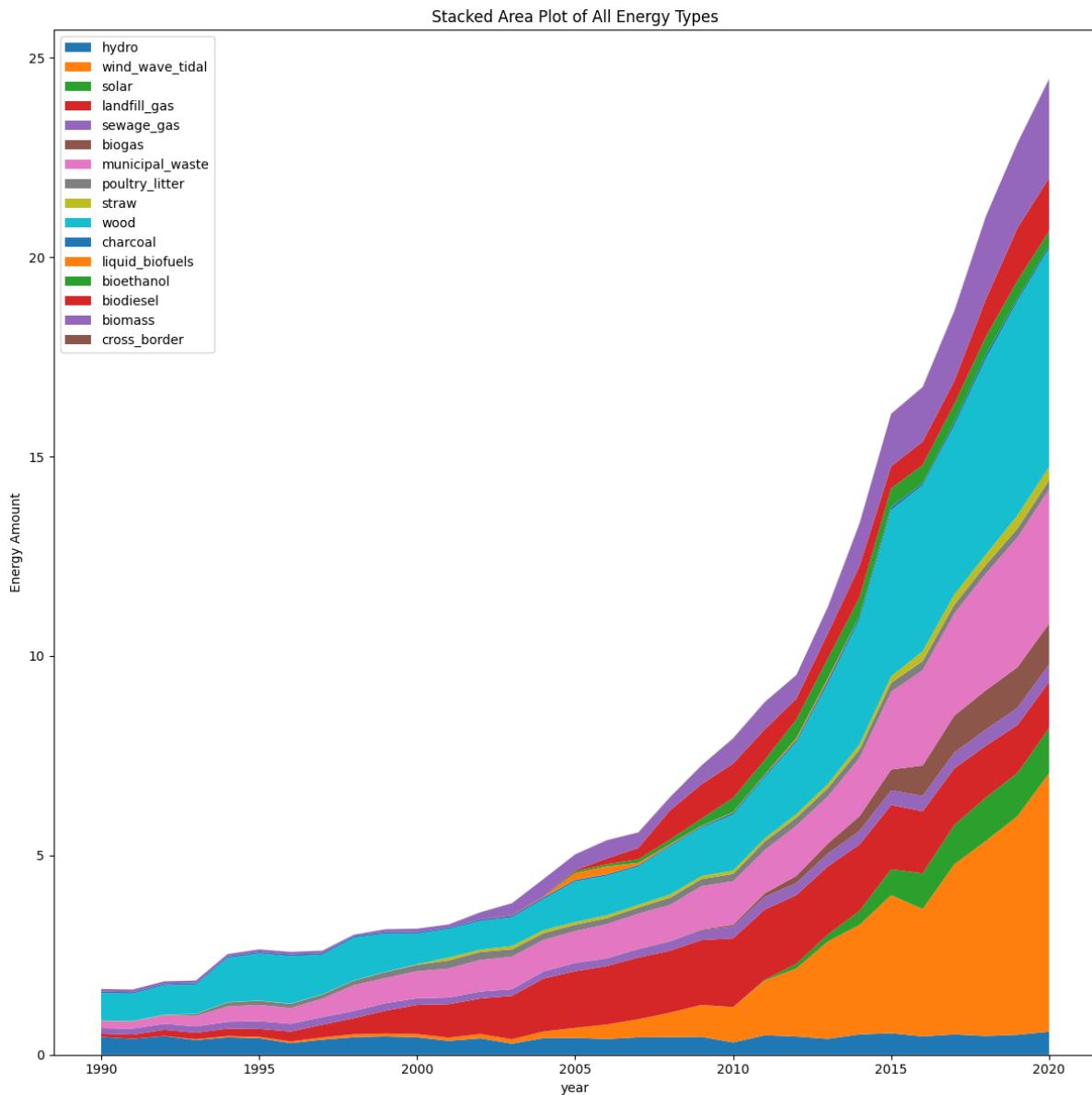
**Figure 7.** GDP Growth and Renewable & Waste Energy over years



### 3.3.4 Decomposition of Renewable Energy Subcomponents

Renewable energy consumption has been decomposed at the subcomponent level and visualized using a stacked area plot. Figure 8 shows that the relative importance of some energy types (e.g., wind and solar) has increased over time, while some components have remained relatively constant. This result indicates that the structure of the renewable energy portfolio in the United Kingdom has undergone a transformation over time.

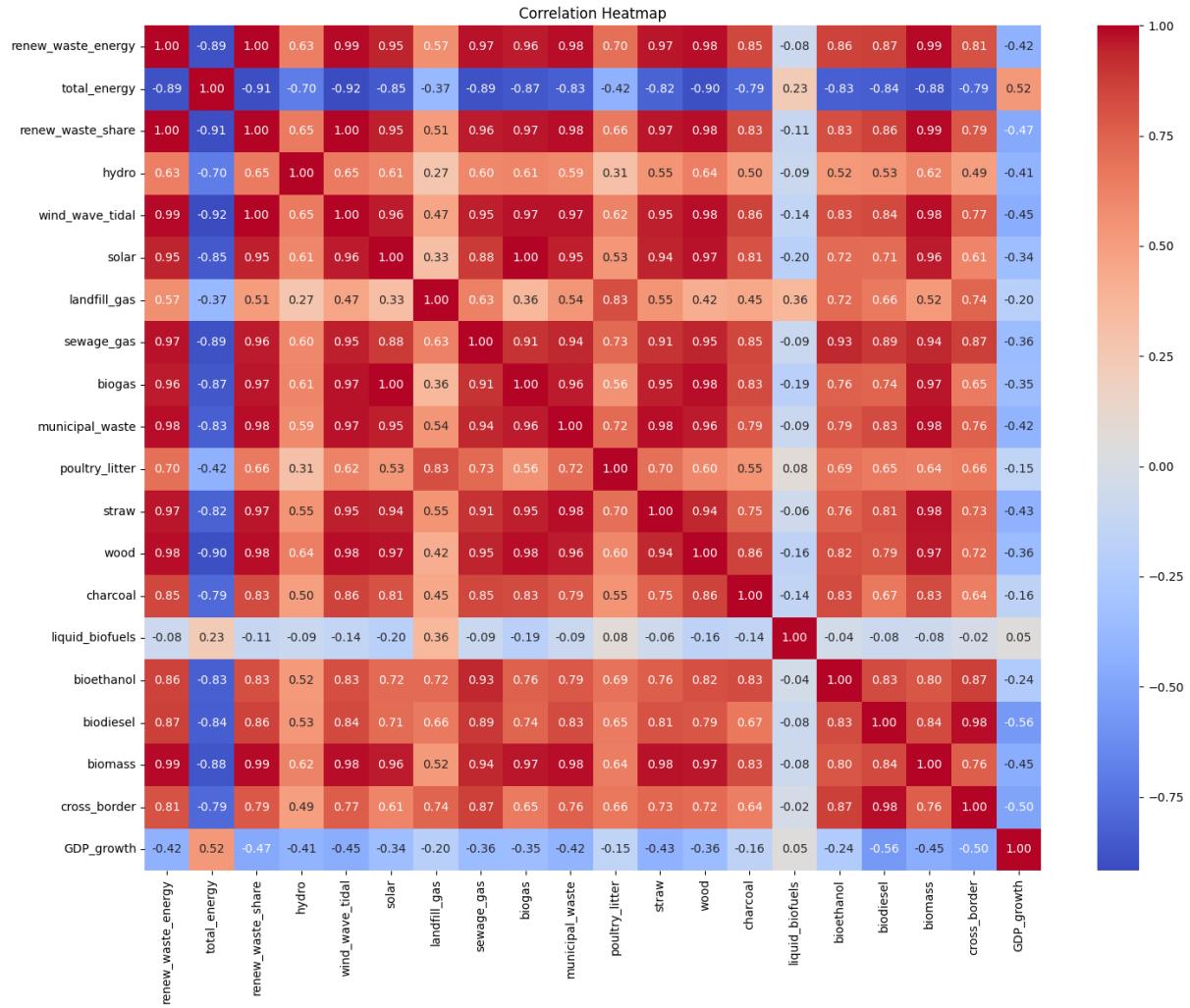
**Figure 8.** Stacked Area Plot of All Energy Types



### 3.4 Correlation Analysis

A correlation matrix was created and visualized with a heat map to examine the linear relationships between economic growth and energy indicators. Figure 9 shows that there are negative relationships between some renewable energy components and GDP growth. This finding indicates that the renewable energy-growth relationship is more complex than previously thought and that linear approaches alone may not be sufficient.

**Figure 9.** Correlation Heatmap



Furthermore, the ranking of the correlation coefficients revealed that total energy consumption has the highest positive correlation with growth, while some renewable components exhibit negative correlations.

### 3.5 Creation of Training and Test Sets

During the modeling phase, the temporal structure was preserved, and the dataset was divided chronologically. In this context, observations from 2015 and earlier were defined as the training dataset, and observations from 2015 onwards were defined as the test dataset. This separation ensures that the learning and performance evaluation of the models on data from different periods are carried out consistently. The training dataset was used to learn the parameters of the classification models; the test dataset was used to measure the classification accuracy and generalizability of the models on previously unseen period data. This approach allows for the evaluation of whether the classification models produce consistent results not only for the period in which they were trained but also in other parts of the dataset.

### 3.6. Modeling Approach and Performance Evaluation

In this study, various regression models were applied to examine the relationship between economic growth and renewable energy indicators. Renewable energy indicators were used as independent variables, while the economic growth variable was modeled as a continuous variable.

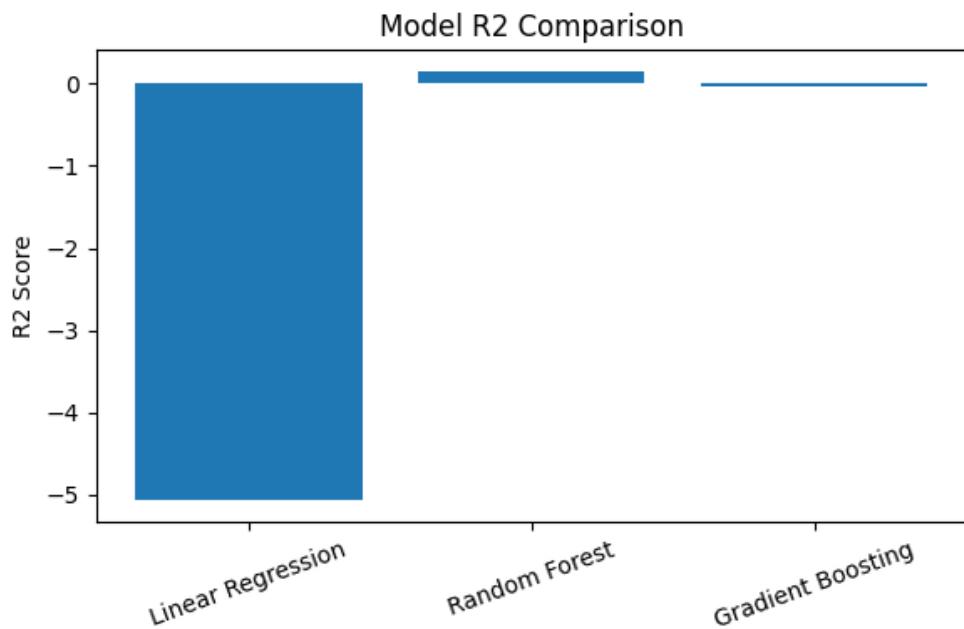
The analysis preferred models capable of capturing both simple linear relationships and more complex nonlinear patterns. This allowed for the simultaneous evaluation of different relationship structures in the dataset.

The success of the established models was evaluated using key performance metrics such as mean absolute error (MAE), root mean square error (RMSE), and  $R^2$  (determination coefficient) on the training and test datasets. Based on the results obtained, the comparative performance of the models was determined, and the most suitable model was identified.

**Table 1.** Model Performance Comparison

Model	MAE	RMSE	$R^2$
<b>Linear Regression</b>	10.3414	11.9372	-5.0705
<b>Random Forest</b>	2.6751	4.4758	0.1466
<b>Gradient Boosting</b>	2.4570	4.9381	-0.0388

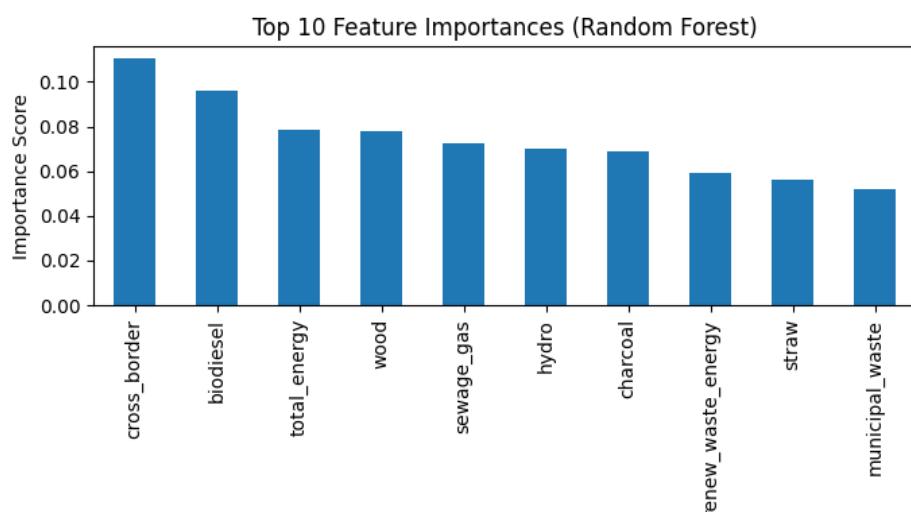
**Figure 10.** Model R2 Comparison



### 3.7. Analysis of Variable Importance Level

Feature importance analysis was performed for the best-performing model, and the results are presented graphically. The graph in Figure 11 shows the energy variables that contribute most to explaining economic growth. These results provide important indicators regarding which renewable energy types should be prioritized in terms of policy design.

**Figure 11.** Top 10 Feature Importances



## 4. Conclusion

This study examined the relationship between renewable and waste-based energy consumption and economic growth in the United Kingdom. The analyses showed that economic growth exhibited a fluctuating pattern and that the impact of renewable energy components was not linear. The Random Forest model provided more accurate predictions compared to the Linear Regression and Gradient Boosting, and feature significance analysis within the model revealed that wind, solar, and hydroelectric energy had a stronger impact on economic growth than other energy types. The study demonstrates that the energy-growth relationship is dynamic and that the impact of each energy type can vary; therefore, it is recommended that policymakers develop energy strategies by evaluating them on a type-by-type basis.

## 5. References

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