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Predictors for Green Energy vs. Fossil Fuels: The Case of Industrial Waste and Biogases in European Union Context

Catalin Popescu [1,*] , **Manuela Rozalia Gabor** [2,3] and **Adrian Stancu** [1,*]

1   Department of Business Administration, Faculty of Economic Sciences, Petroleum-Gas University of Ploiesti, 100680 Ploiesti, Romania
2   Department ED1—Economic Sciences, Faculty of Economics and Law, "George Emil Palade" University of Medicine, Pharmacy, Sciences and Technology of Târgu Mures, 540139 Tîrgu Mures, Romania; manuela.gabor@umfst.ro
3   Department of Economic Research, U.C.S.D.T., "George Emil Palade" University of Medicine, Pharmacy, Sciences and Technology of Târgu Mures, 540139 Tîrgu Mures, Romania
*   Correspondence: cpopescu@upg-ploiesti.ro (C.P.); astancu@upg-ploiesti.ro (A.S.)

Abstract: In the context of sustainability, the integration of renewable energy into industrial processes not only minimizes dependence on fossil fuels but also contributes to the efficient management of industrial waste. By transforming organic waste, including agri-food and urban waste, into biogas, green energy can be generated, thus reducing the impact on the environment and closing the loop of material used in the economic circuit. Thus, a sustainable system can be promoted, where resources are continuously reused and exploited. Statistical methods and a decision tree with the Classification and Regression Trees (CRT) algorithm were employed to analyze data. The paper focuses on the importance of industrial waste and biogas for the generation, transformation, and consumption of energy in the EU (European Union)-27 countries. To provide a thorough analysis, we have divided these countries based on real gross domestic product (GDP) per capita, grouping them above/below the annual average for the period 2012–2021/2022. Descriptive statistics revealed observable differences between the two groups, but the paper aimed to provide evidence regarding the existence of these differences as statistically significant. Using the Kolmogorov–Smirnov test, the non-normal distribution of the data was confirmed, requiring non-parametric inferential methods. The Mann–Whitney U test revealed statistically significant differences between the two groups for all the studied variables. This comprehensive approach highlights the distinct energy-related characteristics influenced by economic development in the EU-27.

Keywords: predictors; renewable energy; waste valorization; industrial waste; biogases; energy production; energy consumption; real GDP/capita; economic development; EU-27 countries

1. Introduction

1.1. Types of Energy Resources

In the last 50 years, the increase in the world population from 3,767,930,001 people in 1971 to 7,888,305,693 in 2021 [1] accordingly determined a rise in consumers' demands for goods and services. To satisfy the increasing demand, companies needed more energy to produce these products and services. Moreover, energy consumption also went up due to the expansion of household numbers and sizes, from 176,913.355 PJ in 1971 to 422,118.519 PJ in 2021 [2]. Thus, even if the growth rate of the population was 109.35%, the increased rate of energy consumption was much higher at 138.6%.

The weight of energy sources has changed in the last 50 years (Figure 1). The highest increase was recorded by heat (978.07%, as compared to 1991, where this is the first record), followed by nuclear energy (878.43%), natural gas (48.5%), renewables and waste (16.61%), and coal, peat, and oil shale (7.05%).

Figure 1. Weight of energy sources in 1971 and 2021. Source: Made by the authors based on data from [2].

In 2015, all United Nations Member States adopted the Sustainable Development Goals (SDGs), which comprise 17 goals to build a sustainable society. The seventh goal, named "Affordable and clean energy", has five targets that follow by 2023. These are to extend the share and use of renewable energy and make it accessible and affordable, to upgrade energy infrastructure to provide modern and sustainable services, and to enhance energy efficiency [3].

According to the International Energy Agency (IEA), renewable energy sources are hydro, solar photovoltaic (PV), bioenergy, wind (onshore and offshore), tide, wave, and ocean, geothermal, solar thermal, and hydrogen. In 2020, the highest weight of the world's gross electricity production by renewable energy sources was registered by wind (43.93%), hydro (28.6%), solar PV (18.52%), bioenergy (6.68%), and geothermal (1.96%) [4,5].

Bioenergy is the energy produced from organic materials, known as biomass, such as forestry products and residues, energy crops, crop residues, municipal solid waste, livestock manure, and wastewater [6]. The IEA groups the statistical data on bioenergy into five categories: industrial waste, municipal waste, primary solid biofuels, liquid biofuels, and biogases [5]. This paper focuses only on industrial waste and biogases, because the IEA database provides complete information only for these two categories.

This paper aims to identify the best predictors for a sustainable system that could be promoted in the case of continuously reused and exploited resources by using complementary, complex statistical methods and machine learning (decision tree with the Classification and Regression Trees (CRT) algorithm) on statistical data for EU-27 countries grouped according to real gross domestic product (GDP) per capita, above/below the annual average for the period 2012–2021/2022, respectively. The paper focuses on the importance of industrial waste and biogas for the generation, transformation, and consumption of energy in the EU-27 countries.

1.2. Industrial Waste

Industrial waste includes energy from the industrial, agriculture, zootechnical, medical, etc. sectors. This waste is heterogeneous, because it emerges from various sources.

Kalak [7] discusses the utilization of biomass for energy production, highlighting its environmental benefits, cost-effectiveness, local abundance, and employment potential in rural areas. The paper explores various types of biomass and their physicochemical properties, particularly waste plant feedstocks, as viable energy sources. Conversion methods like mechanical, thermal, and biochemical processes are analyzed, underscoring their role in generating electricity and heat competitively. Understanding biomass properties is pivotal for optimizing energy production, reducing reliance on fossil fuels, and promoting sustainable energy practices. The study shows the significance of waste biomass as a

renewable energy source, emphasizing its potential to reshape the global energy landscape towards more sustainable alternatives.

Adeleke et al. [8] examine the potential of waste-to-energy (WtE) technologies in Africa, focusing on South Africa, which has the highest theoretical energy potential on the continent. Similar research was performed by Odejobi et al. [9] in the case of Nigeria, which has a close capacity to produce energy from waste. This can be achieved by implementing effective policies and regulations, developing integrated waste management strategies, and promoting awareness and investment in renewable energy technologies to remove the barriers, for instance, low access to funding, lack of technical know-how, a weak grid network, low waste segregation, etc.

Numerous studies [10–15] present the methods used for hydrogen production, known as biohydrogen or biological hydrogen, from agricultural waste (lignocellulosic biomass, food waste, fruit byproducts, etc.). Thus, *Clostridium* spp., *Enterobacter* spp., and *Bacillus* spp. are employed for the dark fermentation of carbohydrate-rich materials in the absence of light and oxygen. To increase hydrogen production, pretreatment methods such as ultrasonication, heat, aeration, acid or base processing, electroporation, etc. can be used. Photosynthetic non-sulfur bacteria (PNS) apply photofermentation, whereas anaerobic fermentation employs apple pomace to obtain hydrogen. The economic analysis of these methods shows that they are more cost-effective than conventional techniques.

Other researchers [16,17] focus on microbial electrochemical technologies (METs) that are based on the principle of converting chemical energy from organic matter into energy, known as microbial fuel cells (MFCs). METs have three versions. The first is the sediment-microbial fuel cell (S-MFC), which generates energy by harnessing microbial metabolism in sediment, where the microorganisms oxidize organic matter, releasing electrons that travel to an anode. Furthermore, the electrons flow through an external circuit to a cathode, combining with protons and oxygen to produce electricity. The second is the plant-microbial fuel cell (P-MFC), in which energy is created through the interaction between plant roots and microbial communities in the soil. Plant roots release organic compounds into the soil, which are then metabolized by microorganisms. This microbial metabolism produces electrons that are harvested by electrodes to generate electrical power. The third is the constructed wetlands-microbial fuel cell (CW-MFC), which produces energy by harnessing microbial activity in wetland soils. Wetland plants and organic matter provide substrates for microbial metabolism, releasing electrons that are captured by electrodes, thus generating electrical energy.
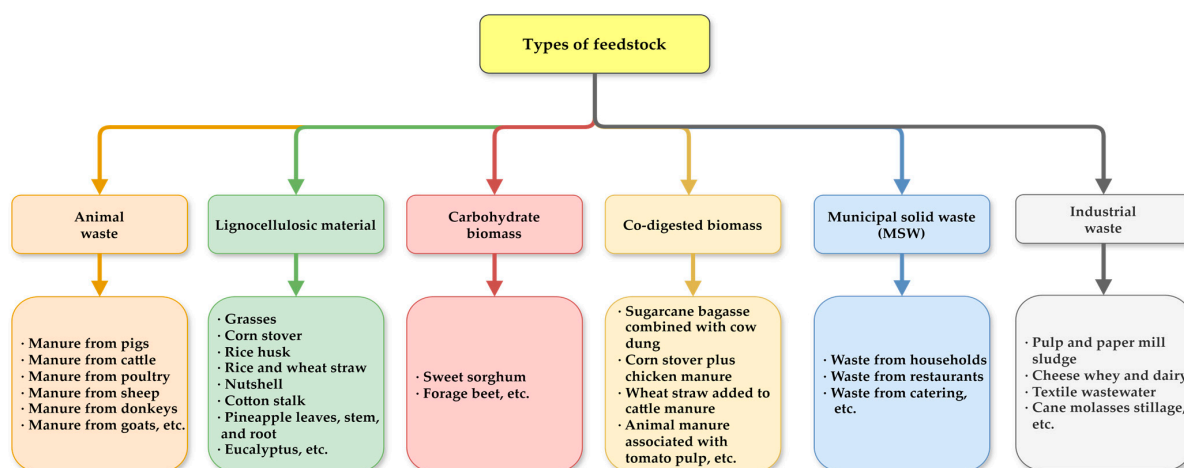
Surveys conducted in the treatment of industrial wastewater show that using bioelectrochemical systems (BES) to eliminate boron from synthetic solutions and geothermal waters can also produce energy with the exploitation of microbial desalination cells (MDCs) [18,19]. Furthermore, Cusick et al. [20] developed the Microbial Reverse-Electrodialysis Cell (MREC) for both wastewater treatment and hydrogen production by capturing salinity-gradient energy.

The waste originating from livestock (including animal manure and animal bedding straw) in the zootechnical sector can also be converted into energy. Biohydrogen is obtained from animal bedding straw, as in the case of carbohydrate-rich materials. Biodiesel is produced from animal manure due to its high moisture content, by going through the following operations: drying, extraction of liquid, separation from impurities, transesterification of the extract, and purification [21].

As regards COVID-19-related medical wastes (CMWs), recent studies [22,23] emphasize that they can be used to produce energy. The production of refuse-derived fuel (RDF) employs different thermochemical conversion methods according to the type of CMW, namely, gasification, plasma gasification, hydrothermal carbonization, pyrolysis, etc. These operations need pretreatment techniques, i.e., disinfection due to the contagious properties of CMWs and torrefaction (dry carbonization).

1.3. Biogas

Biogas consists of a combination of methane and carbon dioxide in high weights and hydrogen, oxygen, nitrogen, hydrogen sulfide, ammonia, etc. in a small proportion. The methane yield in the biogas is in the following descending order according to the main chemical compound of the feedstock, i.e., lipid-, protein-, or carbohydrate-based. The main categories of feedstock used to obtain methane are shown in Figure 2. As for the production technologies, there are three paths, namely, conventional anaerobic digestion (AD), novel AD, and anaerobic degradation in landfills [24–26].

Figure 2. Types of feedstock used to obtain methane. Source: Made by authors based on [24–26].

AL-Huqail et al. [27] experimented to obtain biogas from a mix of peel wastes from four different fruits (kinnow, pineapple, pomegranate, and lemon) and cow dung by comparing a conventional AD and an electro-assisted AD. The conclusions show that the highest volume of methane was produced from pineapple peel waste and with an electro-assisted AD. Furthermore, the AD digestate was leveraged as a soil biofertilizer for radishes, with positive results.

Mavridis et al. [28] make a comparative analysis between the AD and landfill processes for obtaining biogas from the organic part of MSW. Each technology was assessed by taking into account the legal, economic efficiency, technological, and environmental impact perspectives. The findings suggest that AD has more advantages as opposed to landfills. However, landfills are suitable when low quantities of biogas are produced and when the budget is limited for construction and operation.

Kasinath et al. [29] focus on examining the profitability of the AD method employed in generating methane from both feedstocks (such as wheat, maize, bagasse, sugar beet, rye, rice, and their husks, grass, manure from pigs, cattle, and poultry, and sewage sludge) and mixed biomass (for instance, fish waste plus sisal pulp, cattle manure added to distillery wastewater, microalgae with wheat straw, sewage sludge, food waste, etc.). The influence of feedstocks and mixed biomass pretreatments was also studied. Thus, all operations in the AD process should be monitored and controlled to ensure the efficiency of biogas production due to particular influence factors.

Stürmer et al. [30] studied the management of 243 biogas plants from Austria, 100 from Switzerland, and 231 from Germany, with an installed capacity between 95 kW and 890 kW. The feedstocks consist mainly of manure (82%) and biogenic waste (12%) in Switzerland, manure (48%) and maize (43%) in Germany, manure (51%) and biogenic waste (32%) in Western Austria, and maize (39%), manure (17%), and biogenic waste (12%) in Eastern Austria. The results show that the differences in biomass are based on the specific regulations in each of the three countries, and the smaller biogas plants are more efficient than the bigger ones. The authors emphasize the importance of the legal framework and its upcoming changes that might support the future development of biogas production.

O'Connor et al. [31] advocate expanding small-scale anaerobic digestion (SSAD) to other countries. SSAD plants generate between 15 and 99 kW, and they are appropriate for small farms and towns by converting manure and MW into biogas. Germany, Belgium, and Sweden are the leading countries concerning the implementation of SSAD plants. The limitations in adopting SSAD are low national government support schemes and dedicated legislation, insufficient funding, lack of expertise, and insufficient correct information provided to the public about both the advantages and disadvantages of SSAD to create an accurate perception. Other studies [32,33] used mathematical modeling to choose the optimal location for biogas plants in Turkey, taking into account multiple restrictions, and to calculate the methane production potential that can be generated from animal and slaughterhouse wastes using computing methods.

1.4. Future Trends and Limitations of Bioenergy

Nowadays, artificial intelligence (AI) is used in numerous broad and narrow domains such as education [34], psychology [35], the economy [36,37], public administration [38], medicine [39], computer science [40], and nuclear energy [41], including bioenergy. For instance, Jin et al. [42] used machine learning (ML) algorithms to simulate the production of biodiesel from given inputs (reaction temperature, the catalyst–oil mass ratio, etc.) and output as the efficiency of the process. Furthermore, Senocak et al. [43] employed AI to establish the feedstocks that can be used as biomass in a certain region and to predict the estimated energy yield of the feedstocks for 3 years.

Sahoo et al. [44] applied artificial neural network (ANN) modeling to forecast the available energy of the bio-oil and biochar that can be generated from the thermal pyrolysis of *Vachellia nilotica* L. Similar research was conducted by Singh et al. [45] that uses am ANN for measuring the heating level of raw biomass, whereas Pereira et al. [46] used a union of an ANN and Particle Swarm Optimization (PSO) to enhance the operational efficiency of bioethanol output.

Based on ANN and satellite images, Carrijo et al. [47] determined the energy potential of cerradão vegetation feedstock by collecting and analyzing various vegetation indices. Additionally, Cinar et al. [48] stress the benefits of AI technology implementation in the processes of a biogas plant, especially in monitoring the reactions, parameters of the operations, and quantity of biogas produced.

Even if the positive impact of bioenergy on air quality and human health is unquestionable [49], there are also some limitations underscored by some studies. Firstly, the seasonality of some vegetable biomass can introduce variation in energy production. Secondly, several technologies consume more energy than output. Thirdly, increased water consumption is necessary for irrigating the fields cultivated for biomass. Fourthly, various technologies require significant investment: for instance, AD needs additional operations to remove or diminish the dangerous components that are formed together with the biogas. Fifthly, foreign companies and local authorities present land-grabbing issues. Sixth, there is low food security in less-developed countries that use the fields to produce biomass instead of food, which increases the food price and generates slight soil degradation [50–55].

The paper is organized into four sections. Section 2 describes the methodology of the research. The results and discussion are detailed in Section 3. Section 4 details the conclusions and future work.

2. Materials and Methods

In this sub-section, we will present the collected data, variables, and statistical and machine learning methods applied in this research detailing the motivation of the application of specific statistical and machine learning methods for our analysis. With regards to the variables included in the research, both categorical and continuous variables are used only for industrial waste and biogases. The significance of each indicator is retrieved according to the Energy Statistics Manual [56]. Those variables with missing data were removed from the analysis. Data were collected for the 2012–2021/2022 period from Eurostat [57] and

the Energy Statistics Data Browser [5] for all European Union countries (EU-27 countries) as follows:

- *Categorical variable*:
  - ○ Country from EU-27 (2020);
  - ○ Real GDP/capita (with the codification applied in SPSS 29.0 licensed software): 1 = below average EU yearly, 2 = above average EU yearly.
- *Continuous variables*:
  - ○ Real GDP/capita;
  - ○ Gross electricity production (GEP);
  - ○ Gross heat production (GHP);
  - ○ Production—total (PT);
  - ○ Production—imports (PI);
  - ○ Production—exports (PE);
  - ○ Production—stock exchange (PSE);
  - ○ Production—domestic supply (PDS);
  - ○ Transformation—total (TT);
  - ○ Transformation—electricity plants (TEP);
  - ○ Transformation—CHP plants (TCHPP);
  - ○ Transformation—heat plants (THP);
  - ○ Transformation—other transformation (TOT);
  - ○ Energy industry own use—total (EIOU);
  - ○ Final consumption—total (FC);
  - ○ Final consumption—industry (FCI);
  - ○ Final consumption—transport (FCT);
  - ○ Final consumption—residential (FCR);
  - ○ Final consumption—commercial and public services (FCCPC);
  - ○ Final consumption—agriculture/forestry (FCA).

All the data were tested for normal distribution with *one sample Kolmogorov–Smirnov test*: (1) for industrial waste data, none of the variables have a normal distribution, and (2) for biogases, the data have a normal distribution only for production—exports, transformation—other transformation, and final consumption—residential. The non-parametrical statistical methods are justified for our analysis.

For the actual analysis, a complex quantitative approach was applied using complementary statistical methods and machine learning methods, as follows:

- *The descriptive statistics* were used as mean ± standard deviation (minimum-maximum) for the continuous variables. By using descriptive statistics indicators, the extent to which differences and/or similarities occur can be observed, on the one hand, and the other hand, the chosen combination of statistical methods and machine learning methods is justified for the quantitative analysis as the core approach for all the research.
- To find out whether there is any statistically significant association between variables, the *Pearson correlation coefficients* were used to analyze the direction and intensity of the associations between these continuous variables inside each group of countries (</>EU average based on real GDP/capita), separately, for industrial waste and biogases. Only the statistical significance correlations were retained for p-value < 0.05.
- Inferential statistic tests were applied [58] to test whether there are statistically significant differences between the two groups of European Union countries (above average/below average of EU-27 based on real GDP/capita) referring to all variables from the study, separately, for industrial waste and biogases. The *independent samples Mann–Whitney U test* was used for the categorial variables used for comparisons, with p-value < 0.05.
- A machine learning analysis based on the decision tree with CRT "growing method" was applied to find out which variables from the study could be grouped/separated

better among EU-27 countries with real GDP/capita below/above the EU average. The statistical hypothesis for decision tree H_0 is as follows: *Variables are independent*. The alternative hypothesis, H_1, states the following: *The variables are dependent*. The main motivation for applying the *decision tree* with *CRT* is directly linked to the numerous advantages of this method, especially to the advantages of using decision tree compared to classical statistical methods [59–62], which are as follows: (1) the decision tree with CRT algorithm takes into consideration and presents the normalized importance of the independent variables; (2) it allows for the prediction of countries belonging to distinct categories based on their measures according to one or more predictor variables; (3) it allows for the utilization of both categorical or continuous types of data by using different algorithms (CHAID—Chi-square automatic interaction detection, CRT); (4) it groups/classifies the individuals/ideas into homogenous groups by one or more independent variables according to the importance of their contribution to the grouping process. Another important advantage of the decision tree is linked to the graphical representation of these groups and nodes based on the contribution of each independent variable to their formation.

For the statistical analysis, SPSS 23.0 software (licensed) was used. For statistical significance, a threshold of *p*-value < 0.05 was considered for inferential statistical methods. All these results are presented in detail in the next section.

3. Results and Discussion

Through the International Energy Agency website, using Energy Statistics Data Browser 2023, an impressive Excel file containing data for all 27 countries from the EU was generated for the period 2012–2022.

By screening data and comparing information for different issues (industrial waste, municipal waste, solid biofuels, liquid biofuels, biogases, etc.), it was decided to include only two variables in the methodology, namely, industrial waste and biogases. The decision was based on two reasons:

- Data for these two variables are by far the most numerous and complete of all the other analyzed categories;
- The inclusion of all potential variables (already mentioned above) would require a very complicated analysis due to the nature of the data volume involved; in some places, the data cannot be unitarily compared to the other two components already included. This is the case when there is some missing information (in the case of some countries, some years, etc.), and this aspect can negatively influence the findings generated through the analysis for the industrial waste and biogas variables.

3.1. Industrial Waste

The descriptive statistics for all variables from the study for EU-27 countries with yearly real GDP/capita above (green background color) and below (blue background color) the EU-27 average are presented in Table 1.

Table 1. Descriptive statistics in the case of industrial waste.

Variables	<EU-27 Average					>EU-27 Average				
	Mean	Median	Std. Deviation	Minimum	Maximum	Mean	Median	Std. Deviation	Minimum	Maximum
Real GDP/capita	15,632.06	14,920.00	7508.82	5390.00	81,940	41,793.10	36,220.00	15,768.19	25,620.00	86,540.00
GEP	51.89	16.00	69.22	0.00	345.00	312.14	181.00	378.95	6.00	1604.00
GHP	245.52	184.50	217.08	1.00	1281.00	1595.04	748.00	2114.85	38.00	9741.00
PT	5004.83	2395.00	6241.03	9.00	28,437.00	13,739.40	12,156.00	15,844.16	546.00	59,472.00
PI	742.79	330.00	842.65	1.00	3369.00					
PSE	5.20	1.00	57.73	−142.00	171.00	50,887.00	49,437.00	5212.80	44,922.00	59,472.00
PDS	5215.65	2597.00	6203.12	11.00	28,437.00	9989.49	12,156.00	8246.19	546.00	30,439.00
TT	733.45	410.00	801.48	1.00	4811.00	3964.65	3274.50	2710.18	126.00	11,569.00

Table 1. *Cont.*

Variables	<EU-27 Average					>EU-27 Average				
	Mean	Median	Std. Deviation	Minimum	Maximum	Mean	Median	Std. Deviation	Minimum	Maximum
TEP	560.64	274.50	915.92	0.00	4806.00	2511.30	848.00	3794.81	0.00	15,764.00
TCHPP	439.34	335.00	362.27	5.00	1758.00	2420.88	1735.00	1877.04	222.00	6253.00
THP	238.20	178.50	240.92	1.00	938.00	546.38	605.00	439.68	27.00	1367.00
EIOU	524.15	284.00	711.87	1.00	2828.00	3691.83	1936.00	2653.37	597.00	7564.00
FC	5118.27	2702.00	6020.05	2.00	27,296.00	9410.53	6349.00	9706.78	105.00	32,173.00
FCI	6340.35	4005.00	6229.20	44.00	27,159.00	9657.76	7411.50	10,128.03	105.00	32,173.00
FCCPS	3280.58	167.00	4522.79	1.00	11,291.00	396.36	111.00	504.74	8.00	1200.00

Due to the evident differences between means and medians from Table 1 of each group of EU-27 countries, we applied the *independent samples Mann–Whitney U test* to compare sample means and evaluate whether there are statistically significant differences between these groups of EU-27 countries.

The results are presented in Table 2 only for variables with no differences (FCI and FCCPS). They indicate that for all the rest of the variables from the study, for industrial waste, statistically significant differences exist between the two groups of countries.

Table 2. Results of independent samples Mann–Whitney U test for industrial waste.

Null Hypothesis	Test	Sig. [a,b]	Decision
The distribution of FCI is the same across categories under/above the yearly mean of GDP for EU-27 (from 2020).	Independent samples Mann–Whitney U test	0.160	Retain the null hypothesis.
The distribution of FCCPS is the same across categories under/above the yearly mean of GDP for EU-27 (from 2020).	Independent samples Mann–Whitney U test	0.050	Retain the null hypothesis.

[a]. The significance level is 0.050. [b]. Asymptotic significance is displayed.

The results of Pearson correlation coefficients are presented in Table 3 for each group of EU-27 countries.

Table 3. Pearson's correlation coefficients in the case of industrial waste.

Under/Above the Yearly Mean of GDP for EU-27 (from 2020)			Real GDP/Capita	GEP	GHP	PT	TT	EIOU	FC
<EU mean/year	Real GDP/capita	Pearson Correlation	1	0.233 *	0.212 *	0.102	0.442 **	−0.424 **	0.078
		Sig. (2-tailed)		0.014	0.045	0.193	<0.001	0.003	0.351
		N	165	110	90	163	112	48	147
	GEP	Pearson Correlation		1	0.533 **	0.151	0.873 **	−0.485 *	0.149
		Sig. (2-tailed)			<0.001	0.116	<0.001	0.041	0.149
		N		110	77	110	99	18	95
	GHP	Pearson Correlation			1	0.530 **	0.706 **	−0.283	0.503 **
		Sig. (2-tailed)				<0.001	<0.001	0.227	<0.001
		N			90	90	85	20	83
	PT	Pearson Correlation				1	0.332 **	−0.334 *	0.993 **
		Sig. (2-tailed)					<0.001	0.020	<0.001
		N				163	112	48	147
	TT	Pearson Correlation					1	−0.418	0.240 *
		Sig. (2-tailed)						0.084	0.016
		N					112	18	100
	EIOU	Pearson Correlation						1	−0.351 *
		Sig. (2-tailed)							0.015
		N						48	47
	FC	Pearson Correlation							1
		Sig. (2-tailed)							
		N							147

Table 3. *Cont.*

Under/Above the Yearly Mean of GDP for EU-27 (from 2020)			Real GDP/Capita	GEP	GHP	PT	TT	EIOU	FC
>EU mean/year	Real GDP/capita	Pearson Correlation	1	−0.262 *	−0.145	−0.386 **	−0.232	−0.804 **	−0.416 **
		Sig. (2-tailed)		0.022	0.209	<0.001	0.057	<0.001	<0.001
		N	87	77	77	87	68	18	79
	GEP	Pearson Correlation		1	0.923 **	0.934 **	0.883 **	0.849 **	0.814 **
		Sig. (2-tailed)			<0.001	<0.001	<0.001	<0.001	<0.001
		N		77	77	77	68	18	69
	GHP	Pearson Correlation			1	0.917 **	0.717 **	−0.753 **	0.833 **
		Sig. (2-tailed)				<0.001	<0.001	<0.001	<0.001
		N			77	77	68	18	69
	PT	Pearson Correlation				1	0.799 **	−0.782 **	0.970 **
		Sig. (2-tailed)					<0.001	<0.001	<0.001
		N				87	68	18	79
	TT	Pearson Correlation					1	0.751 **	0.669 **
		Sig. (2-tailed)						<0.001	<0.001
		N					68	18	68
	EIOU	Pearson Correlation						1	−0.938 **
		Sig. (2-tailed)							<0.001
		N						18	18
	FC	Pearson Correlation							1
		Sig. (2-tailed)							
		N							79

*. Correlation is significant at the 0.05 level (2-tailed). **. Correlation is significant at the 0.01 level (2-tailed).

From the correlation matrices (Table 3) for European countries with GDP/capita below the EU-27 average for the period analyzed (2012–2022), there are statistically significant correlations (*p*-value < 0.05) as follows:

- Direct correlations of strong intensity between PT and FC (+0.993) and between GEP and TT (+0.873);
- Medium direct correlations between GHP and PT (+0.530), GHP and FC (+0.503), and real GDP/capita and TT (+0.442);
- Inverse correlations of medium intensity between real GDP/capita and EIOU (−0.424), GHP and EIOU (−0.485), and TT and EIOU (−0.418).

From the correlation matrices above for European countries with GDP/capita higher than the EU-27 average for the period analyzed (2012–2022), there are statistically significant correlations (*p*-value < 0.05) as follows:

- Direct correlations of strong intensity between GEP and GHP (0.923), GEP and PT (0.934), GEP and FC (+0.814), GEP and TT (+0.883), GEP and EIOU (0.849), GHP and PT (0.917), GHP and FC (+0.833), PT and FC (+0.970), GHP and TT (+0.717), PT and TT (+0.799), and TT and EIOU (+0.751);
- Strong inverse correlations between real GDP/capita and EIOU (−0.804), GHP and EIOU (−0.753), PT and EIOU (−0.782), and EIOU and FC (−0.938).

Figures 3–6 show the distribution of EU-27 countries in each country group (below/above the annual average real GDP/capita) according to the variables in the study and the trend of these indicators for each country group. Thus, for the distribution of GEP according to PT (Figure 3), both groups have an increasing trend, but the group of countries with GDP/capita below the EU-27 average has a slower growth compared to those with a GDP above the EU-27 average.

For the distribution of GHP as a function of PT (Figure 4), both groupings have a somewhat similar upward trend, and therefore quite a similar evolution for the period 2012–2022. For the FC distribution by GEP (Figure 5), both groups have an increasing trend, but the group of countries with GDP/capita below the EU-27 average has a slower growth compared to those with a GDP above the EU-27 average. For the FC by GHP (Figure 6), both groups have an increasing trend, but the group of countries with GDP/capita below the EU-27 average has a very hardly perceptible increase compared to those with a GDP above the EU-27 average.
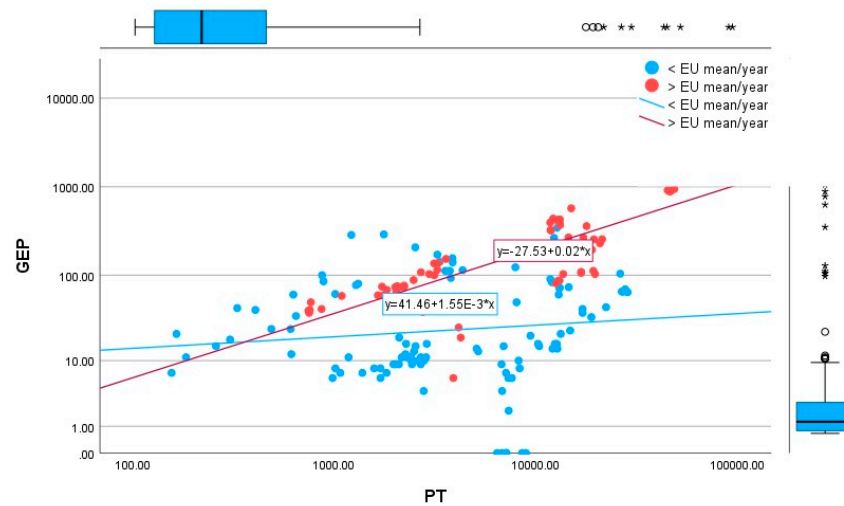
Figure 3. Distribution of EU-27 countries according to GEP to PT for industrial waste.
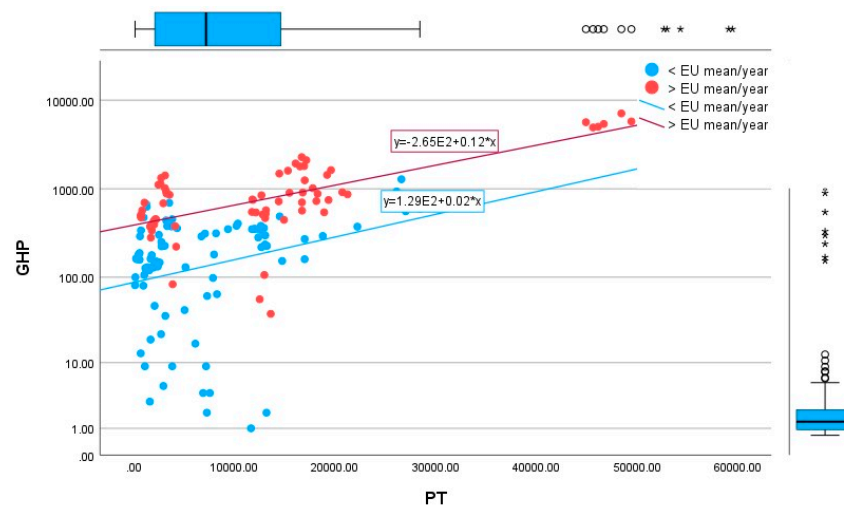

Figure 4. Distribution of EU-27 countries according to GHP to PT for industrial waste.
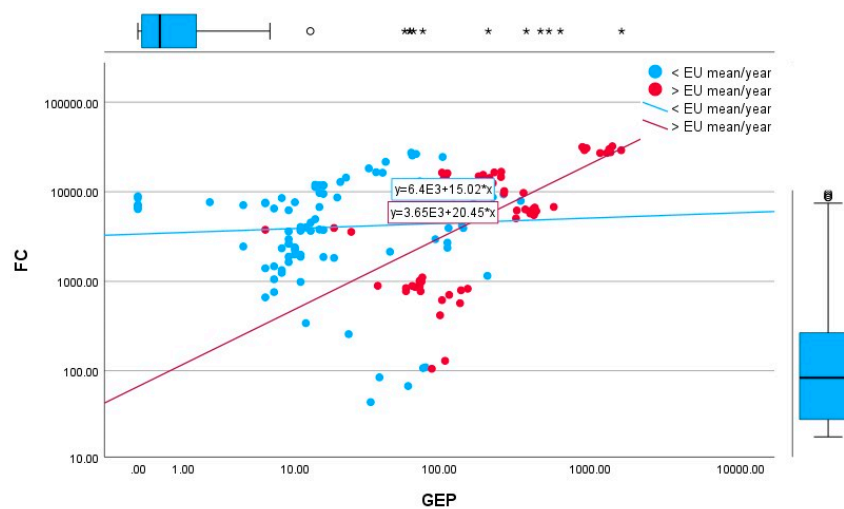

Figure 5. Distribution of EU-27 countries according to FC to GEP for industrial waste.
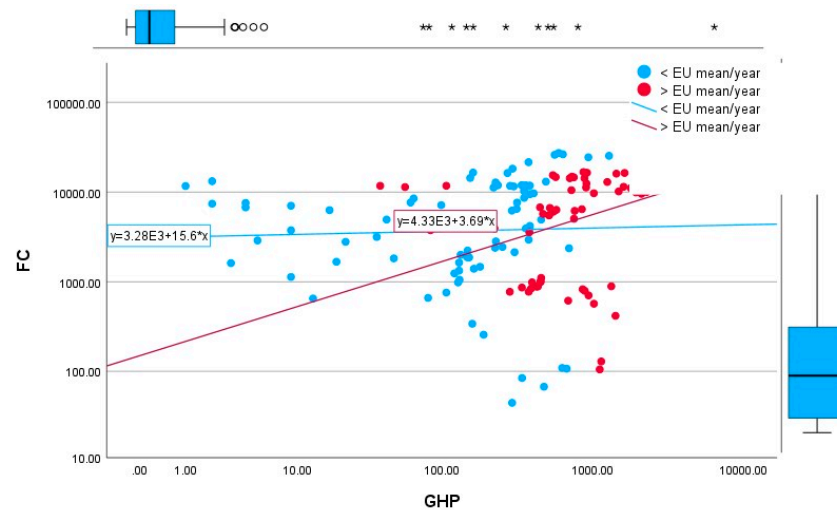
Figure 6. Distribution of EU-27 countries according to FC to GHP for industrial waste.

The results of the decision tree with CRT algorithm (Figure 7) indicate that it is the best predictor for differences between EU-27 countries with yearly GDP/capita above/below the EU-27 average for the variable GEP with a cut-off of 35.5 (Node 1). For those EU-27 countries with real GEP < 35.5, the next best predictor according to decision tree results is the FCI, with the identified cut-off equal to 1016.0.
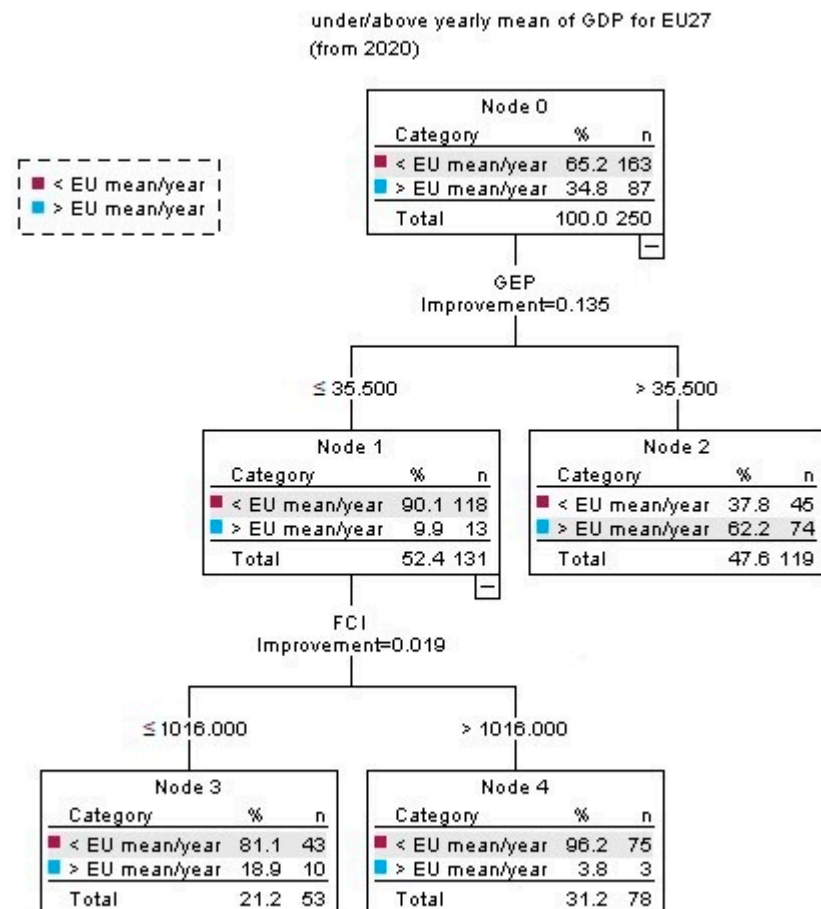

Figure 7. Decision tree results in the case of industrial waste.

3.2. Biogases

The descriptive statistics for all variables from the study for biogases for EU-27 countries with yearly real GDP/capita above/below the EU-27 average are presented in Table 4.

Table 4. Descriptive statistics in the case of biogases.

Variables	<EU-27 Average					>EU-27 Average				
	Mean	Median	Std. Deviation	Minimum	Maximum	Mean	Median	Std. Deviation	Minimum	Maximum
GHP	1221.96	186.00	2648.447	1	12,177	2036.45	526.00	3655.369	46	18,103
PT	10,342.46	3323.00	18,900.855	5	87,007	42,728.31	9089.00	90,514.681	548	325,115
PI	193.58	33.00	337.356	3	1000	79.00	79.00		79	79
PE	−510.40	−491.00	87.500	−687	−393					
PSE	−15.40	31.50	161.305	−410	158					
PDS	10,326.24	3323.00	18,865.954	5	87,007	42,729.03	9089.00	90,514.393	548	325,115
TT	7856.56	2474.00	16,723.638	4	85,520	32,383.95	5841.00	68,811.016	358	248,072
TEP	3014.78	527.00	6831.503	3	30,711	12,635.93	1648.50	24,206.839	1	90,483
TCHPP	5353.52	1223.00	10,689.690	28	55,291	18,352.02	3432.00	43,862.868	182	179,407
THP	503.51	17.00	1022.021	1	2953	192.63	139.00	150.076	1	588
TOT	1094.32	303.00	2002.054	25	7769	3726.01	467.50	7235.062	2	33,549
EIOU	281.08	38.00	713.252	1	4597	7216.65	756.00	9306.207	56	21,429
FC	2464.67	345.50	6073.278	1	42,861	7995.70	3679.00	15,282.926	33	59,721
FCI	1331.04	217.00	3562.582	1	17,055	1276.93	1230.00	942.790	22	3672
FCT	205.64	1.00	331.896	1	1,000	1138.98	59.00	1575.262	1	4960
FCR	8715.80	1543.00	11,825.152	1021	28,680	4839.61	1586.50	5300.883	1	13,156
FCCPC	497.18	129.00	746.924	1	2899	2660.24	770.50	4732.878	2	17,268
FCA	812.57	183.00	1628.567	1	5741	3540.49	183.00	7364.856	1	25,594

Due to the evident differences between means and medians from Table 4 of each group of EU-27 countries, we applied the independent samples Mann–Whitney U test to test whether there are statistically significant differences between these groups of EU-27 countries. The results, presented in Table 5 only for variables with no differences (FCR, FCA, and TOT), indicate that for all the rest of the variables from the study, for industrial waste, statistically significant differences exist between the two groups of countries.

Table 5. Result of independent samples Mann–Whitney U test for biogases.

Null Hypothesis	Test	Sig. [a,b]	Decision
The distribution of TOT is the same across categories under/above the yearly mean of GDP for EU-27 (from 2020).	Independent samples Mann–Whitney U test	0.169	Retain the null hypothesis.
The distribution of FCR is the same across categories under/above the yearly mean of GDP for EU-27 (from 2020).	Independent samples Mann–Whitney U test	0.272	Retain the null hypothesis.
The distribution of FCA is the same across categories under/above the yearly mean of GDP for EU27 (from 2020).	Independent samples Mann–Whitney U test	0.174	Retain the null hypothesis.

[a]. The significance level is 0.050. [b]. Asymptotic significance is displayed.

The results of Pearson correlation coefficients are presented in Table 6 for each group of EU-27 countries.

From Table 6, for European countries with GDP/capita below the EU-27 average for the period analyzed (2012–2022), there are statistically significant correlations (p-value < 0.05) as follows: strong direct correlations between GHP and GEP (+0.840), GEP and PT (+0.914), GEP and TT (+0.986), GHP and PT (+0.946), GHP and TT (+0.946), and PT and TT (+0.948).

Table 6. Pearson's correlation coefficients in the case of biogases.

Under/Above the Yearly Mean of GDP for EU-27 (from 2020)			Real GDP/Capita	GEP	GHP	PT	TT	EIOU	FC
<EU mean/year	Real GDP/capita	Pearson Correlation	--						
		Sig. (2-tailed)							
		N	181						
	GEP	Pearson Correlation	0.317 **	--					
		Sig. (2-tailed)	<0.001						
		N	181	181					
	GHP	Pearson Correlation	0.283 **	0.840 **	--				
		Sig. (2-tailed)	<0.001	<0.001					
		N	144	144	144				
	PT	Pearson Correlation	0.280 **	0.914 **	0.946 **	--			
		Sig. (2-tailed)	<0.001	<0.001	<0.001				
		N	181	181	144	181			
	PP	Pearson Correlation	0.315 **	0.986 **	0.916 **	0.948 **	--		
		Sig. (2-tailed)	<0.001	<0.001	<0.001	<0.001			
		N	179	179	142	179	179		
	EIOU	Pearson Correlation	0.251	0.274	−0.318	0.137	0.105	--	
		Sig. (2-tailed)	0.082	0.057	0.076	0.347	0.472		
		N	49	49	32	49	49	49	
	FC	Pearson Correlation	0.007	0.144	0.418 **	0.511 **	0.212 **	0.023	--
		Sig. (2-tailed)	0.928	0.054	<0.001	<0.001	0.004	0.873	
		N	178	178	141	178	178	49	178
>EU mean/year	Real GDP/capita	Pearson Correlation	--						
		Sig. (2-tailed)							
		N	110						
	GEP	Pearson Correlation	−0.236 *	--					
		Sig. (2-tailed)	0.013						
		N	110	110					
	GHP	Pearson Correlation	−0.261 **	0.876 **	--				
		Sig. (2-tailed)	0.009	<0.001					
		N	99	99	99				
	PT	Pearson Correlation	−0.252 **	0.997 **	0.884 **	--			
		Sig. (2-tailed)	0.008	<0.001	<0.001				
		N	110	110	99	110			
	TT	Pearson Correlation	−0.252 **	0.994 **	0.892 **	0.999 **	--		
		Sig. (2-tailed)	0.008	<0.001	<0.001	<0.001			
		N	110	110	99	110	110		
	EIOU	Pearson Correlation	−0.895 **	0.998 **	0.848 **	0.996 **	0.993 **	--	
		Sig. (2-tailed)	<0.001	<0.001	<0.001	<0.001	<0.001		
		N	31	31	31	31	31	31	
	FC	Pearson Correlation	−0.266 **	0.983 **	0.852 **	0.983 **	0.972 **	0.991 **	--
		Sig. (2-tailed)	0.005	<0.001	<0.001	<0.001	<0.001	<0.001	
		N	109	109	99	109	109	31	109

*. Correlation is significant at the 0.05 level (2-tailed). **. Correlation is significant at the 0.01 level (2-tailed).

Table 6 also shows that for European countries with GDP/capita higher than the EU-27 average for the period analyzed (2012–2022), there are direct correlations of strong intensity that are statistically significant (p-value < 0.05) between all variables except real GDP/capita, but there is also an inverse correlation of strong intensity between real GDP/capita and EIOU (−0.895).

Figures 8–11 show the distribution of European countries in each country group (below/above the annual average real GDP/capita) according to the variables in the study and the trend of these indicators for each country group. Thus, for the distribution of GEP according to PT (Figure 8), both groups have an increasing trend, but the group of countries with GDP/capita below the EU-27 average has a slower growth compared to those with a GDP above the EU-27 average.

According to the results presented in Figure 9, for the distribution of GEP on PT for EU-27 countries, the results for the group of countries below the EU mean were better than those for the EU-27 countries above the European mean for biogases.

As for the distribution of FC on GEP for EU-27 countries (Figure 10), the group of countries below the EU mean had better results than those of countries from the EU-27 above the European mean in the last study period of this research.
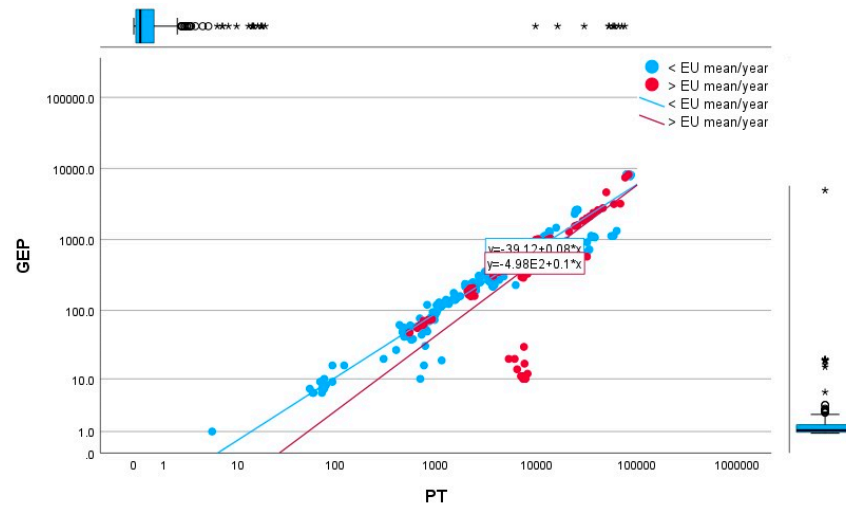
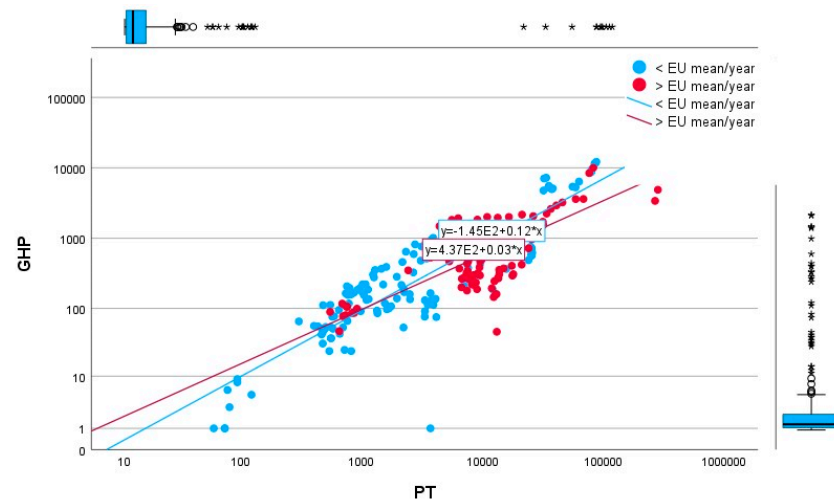**Figure 8.** Distribution of EU-27 countries according to GEP to PT for biogases.

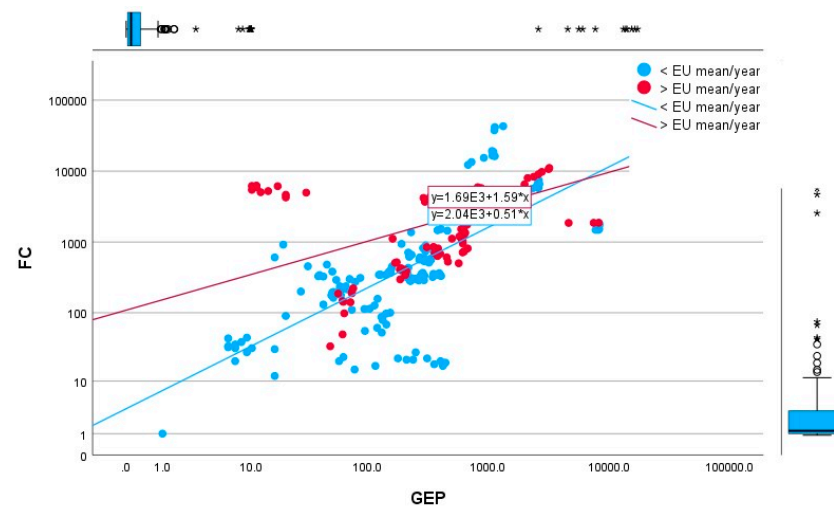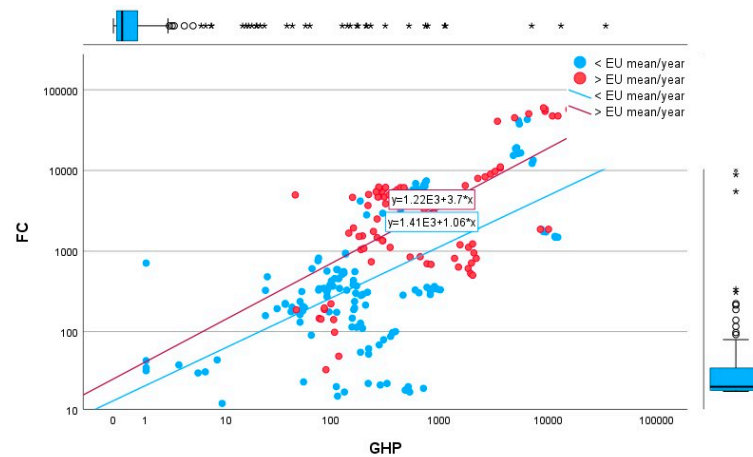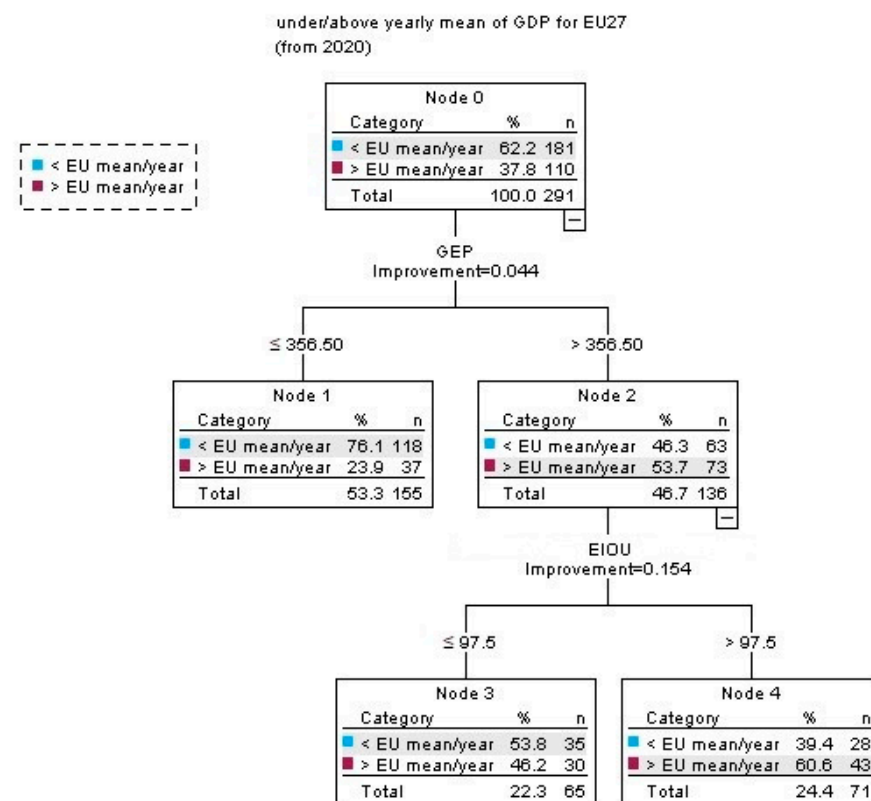**Figure 9.** Distribution of EU-27 countries according to GHP to PT for biogases.

Figure 10. Distribution of EU-27 countries according to FC to GEP for biogases.

Figure 11. Distribution of EU-27 countries according to FC to GHP for biogases.

Figure 11 underscores that the distribution of FC on GHP for both groups of countries above/below the EU mean was comparatively equal for the study period of this research.

The results of the decision tree with the CRT algorithm (Figure 12) indicate the best predictor for differences between EU-27 countries with yearly GDP/capita above/below the EU-27 average for biogases as variable GEP with a cut-off of 356.5 (Node 1). For those EU-27 countries with real GEP < 365.5, the next best predictor according to decision tree results is the EIOU, with an identified cut-off equal to 97.5.

Figure 12. Decision tree results in the case of biogases.

4. Conclusions

Our research results based on applied statistical methods and a decision tree with CRT algorithm (a machine learning method) emphasize important and detailed analysis linked to two important resources for energy generation, transformation, and final consumption, i.e., industrial waste and biogases, for EU-27 countries.

For a deep analysis of EU-27 countries, we decided to split them according to an important macroeconomic indicator for the economic development of EU-27 countries, the real GDP/capita, a yearly average. The countries were grouped into two categories, above and below the GDP/capita yearly average, respectively. Therefore, for the period 2012–2021/2022 (data were not available for some countries), each EU-27 country was grouped based on this variable. The quantitative mathematical differences between these groups of countries were evident from the results of descriptive statistics, but our main purpose was to demonstrate that these differences are statistically significant.

Consequently, complex and complementary statistical methods were applied. Firstly, the descriptive statistics highlight the easily observable differences between the two groups of EU-27 countries. Then, the *Kolmogorov–Smirnov test* shows the non-normal distribution of data, and inferential statistical methods were applied to the non-parametrical data. As such, the *independent samples Mann–Whitney U test* shows statistically significant differences between the two groups of EU-27 countries for all the variables from the research, except the following:

- For industrial waste: FCI and FCCPS;
- For biogases: FCR, FCA, and TOT.

Also, the *Pearson correlation coefficients* show other important aspects for each energy resource, as follows:

- For industrial waste: (1) for European countries with GDP/capita below the EU-27 average, there are direct and strong intensity correlations between PT and FC and between GEP and TT; (2) for European countries with GDP/capita higher the EU-27 average, there is a powerful direct correlation between most of the variables except for real GDP/capita and EIOU, with inverse medium to powerful correlations for all the rest of variables.
- For biogases: (1) for European countries with GDP/capita below the EU-27 average, there are strong direct correlations between GHP and GEP, GEP and PT, GEP and TT, GHP and PT, GHP, and TT, and PT and TT; (2) for European countries with GDP/capita higher the EU-27 average, there are direct and strong intensity correlations between all variables except real GDP/capita, but there is also an inverse correlation of strong intensity between real GDP/capita and EIOU.

The graphical representation of the evolution of GEP and GHP according to production total and FC according to GEP and GHP indicate other important details for two groups of EU-27 countries, respectively:

- For industrial waste: the country distribution and the trend for the two groups of EU-27 countries are quite different, with a slow evolution for the group of EU-27 countries below average GDP, and a quite dynamic trend, with a positive slope for the group of EU-27 countries with higher GDP than average, with the exception of GHP depending by PT, where the evolution is quite similar.
- For biogases: the evolution and trend of GEP and GHP depending on PT is quite similar for both groups of countries, with a positive evolution. It is better for EU-27 countries with higher GDP/capita than for the group of EU-27 countries with lower GDP/capita for the distribution of GHP depending on PT. The trend for FC depending on GHP is also comparatively similar for the two groups of countries.

For more insight into our analysis, and according to the objective of the research, important details were revealed after the decision tree with the CRT algorithm was applied:

- The best predictor for groups of EU-27 countries with an average real GDP/capita per year higher/lower than the EU-27 average for both analyses for industrial waste is the GEP (with the cut-off = 35.5), followed by final consumption—industry (with a cut off = 1016.0), for countries with GEP < 35.5;
- The best predictor for groups of EU-27 countries with an average real GDP/capita per year higher/lower than the EU-27 average for both analyses for biogases is also the

GEP (with the cut off = 356.5), followed by EIOU (with the cut off = 97.5), for countries with GEP > 356.5.

Our results demonstrate different predictors for industrial waste and biogases that are differentiated between groups of EU-27 countries above/below the European mean of real GDP/capita, respectively. With the complimentary use of statistical methods and machine learning methods, our research results practically demonstrate and enrich the existing literature with new insights for a sustainable system that could be promoted in the case of continuously reused and exploited resources.

The complexity of the studied phenomenon necessitates a future focus on analysis and research oriented toward the following elements: the introduction of other variables and the application of other methods such as multi-linear regression, SEM (Structural Equation Modeling), panel regression, etc. In addition, two other useful and interesting aspects have to be considered: the correlation of the indicators with the evolution of the area cultivated with the plants used as energy sources, respectively, for food production; and the correlation of indicators with the evolution of grain imports used to obtain biofuels.

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