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National Carbon Accounting—Analyzing the Impact of Urbanization and Energy-Related Factors upon CO_2 Emissions in Central–Eastern European Countries by Using Machine Learning Algorithms and Panel Data Analysis

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Abstract: The work at hand assesses several driving factors of carbon emissions in terms of urbanization and energy-related parameters on a panel of emerging European economies, between 1990 and 2015. The use of machine learning algorithms and panel data analysis offered the possibility to determine the importance of the input variables by applying three algorithms (Random forest, XGBoost, and AdaBoost) and then by modeling the urbanization and the impact of energy intensity on the carbon emissions. The empirical results confirm the relationship between urbanization and energy intensity on CO_2 emissions. The findings emphasize that separate components of energy consumption affect carbon emissions and, therefore, a transition toward renewable sources for energy needs is desirable. The models from the current study confirm previous studies' observations made for other countries and regions. Urbanization, as a process, has an influence on the carbon emissions more than the actual urban regions do, confirming that all the activities carried out as urbanization efforts are more harmful than the resulted urban area. It is proper to say that the urban areas tend to embrace modern, more green technologies but the road to achieve environmentally friendly urban areas is accompanied by less environmentally friendly industries (such as the cement industry) and a high consumption of nonrenewable energy.

Keywords: urbanization; energy intensity; carbon emissions; environment; energy consumption; CO_2

1. Introduction

Currently, the environmental issues are more critical than ever. The Amazon forest is burning, the glaciers in the north are melting away, and an increasing number of species are threatened by extinction. Some decision-makers are mocking environmentalists, and some are ignorant about the issues, setting targets beyond the planetary boundaries. Still, no real solutions were identified, and all proposed solutions are accompanied by economic costs that not everyone is eager to accept.

The newest urban development trends are related to smart solutions for city life. Whether about waste management or streetlights, the decision-makers are seeking new innovative ways of making the city a "smart" one. Even so, the environmental impact is still an issue that cannot be fully addressed by "smart" solutions. Besides the solid waste and water management, urban emissions (industries and households) are one of the main problems to be solved in the near future, should economies try to reduce pollution in large urban agglomerations. Is "smart" sustainable enough?

The International Energy Agency estimates that about 70 percent of energy-related global greenhouse gases are accountable to urban areas. Because a growth in urban population is expected, the urban environmental impact will consequently grow as well if not properly addressed. However, there are studies contradicting these figures and claiming that small towns, rural areas, deforestation, and modern agriculture contribute more than large urban areas towards global greenhouse emissions [1].

Although the researchers and decision-makers developed accounts and methodologies for GHG emissions, the lack of comparability between them is limited [2,3] and so, the comparability of different policies is as well. Some discrepancies arise even from different interpretations of the concept of "urbanization", and others from the difficulties in properly assessing the impact on the environmental dimension [4]. According to Fang [5], the urbanization process is accompanied by the excessive use and consumption of resources, a fact which affects the environmental sustainability desideratum.

It is important for us to understand the main findings of such studies because of the critical environmental issues and their relationship with human development, including economic growth, demographic growth, energy intensity, energy production sources, energy consumption destinations, and technological development. According to some previous research studies [4,6–13], the process of urbanization is accountable for environmental degradation and established urban areas have harmful impacts on nature through the urban way of life and consumer behavior. It is also critical to understand how different patterns of urbanization, depending on the region, culture, or socio-economic context exist and develop.

The diversity of research related to the impact of urbanization on the environment is also given by different interpretations of the urbanization–carbon emissions relationship. Thus, urbanization could be responsible for emissions since the process relates to high energy consumption due to the economic activities sustaining it. Industrialization, transport agglomeration, consumption behavior, and population migration from less environmentally harmful rural areas must be analyzed also, from the perspective of urbanization as living process. However, some authors [14] analyzed the relationship between electricity consumption, electricity prices, industrial value-added, urbanization population growth, and CO_2 emissions with gross domestic product and revealed that both urbanization and carbon emissions have a short-run effect on economic growth. Thus, urbanization must not be considered a method for improving the economic sustainability. Algarini [15] reported that income, energy consumption, and energy production can be used for predicting CO_2 emissions. However, another study [16] revealed that urbanization must not be tagged as a negative factor in predicting CO_2 emissions since, for example, in oil-abundant economies, oil prices could lead to an acceleration in urbanization, a situation which implies a positive effect on the CO_2 emissions. However, when it reaches an advanced level of development, urbanization is less environmentally harmful, and it seems to even protect it by a complex change in socio-economic behavior.

Urbanization as a process, but also as a way of human life, is strongly connected with high energy demand. According to some studies [17–19], extensive energy consumption, especially non-renewable energy, causes urbanization to decrease environmental quality via increased CO_2 emissions. Also, other authors [20] characterized the urbanization negative effect as being heterogeneous across various quantiles of urban development.

Most researchers take carbon emissions as an indicator for the environment's quality [21–24], mostly due to its relationship with a multitude of economic activities, while other researchers consider the water usage or particulate matter pollution to be as important as the CO_2 emissions [22,25].

Some studies emphasized that direct economic activities (such as cement production) are responsible for the emissions [26,27], while others [9,11–13] revealed that urban economic polarization accompanied by rural population migration to urban areas, high energy consumption, urban agglomerations, fossil fuels, and household emissions are the main drivers of the carbon emissions. However, some studies considered the relation between urbanization and CO_2 emissions as being not very significant or inconclusive [28–31]. Another study [18] suggest that the relationship between urbanization and the environment is not monotonic, and it could have a non-linear effect on the environmental degradation. The setting of new urban and economic development patterns connected to the sustainability goals and the green economy are universally recommended [6,7,25–27]. Also, promoting economic development, increasing the percentage of non-agricultural output, and decreasing discharge of industrial wastewater per capita are measures recommended by other researchers [32] in order to improve the relationship between urbanization and environment.

Some authors [11] consider that even if the urbanization as a process affects the environment, being related to high energy intensity and emissions, altering this urban behavior by promoting environmentally friendly technologies and energy sources could moderate the environmental damage curve.

After analyzing the scientific literature, three major conclusions related to urbanization–environment relationship were identified: (a) Urbanization damages the environment; (b) Urbanization damages the environment only at early stages but later brings beneficial concomitant effects; (c) Urbanization does not damage the environment as much as other factors do.

The first group of studies consider that urbanization damages the environment through rural population relocation to urban areas, accelerated economic growth [13], consumer behavior and transportation [14,15], energy intensity [33] and industrial development based on fossil fuels (coal) [6,7,9]. Thus, this first category of studies either excludes a discussion on the later stages of urbanization or agrees that urbanization affects the environment, no matter at which stage [16,18,26].

The second group of research discusses urbanization as a moving process from the lower stages where the environmental damage is high to later stages where it tends to have attenuated negative effects. Thus, a research study [34,35] emphasizes that the peak of carbon emission occurred at early stages of urbanization for most developed economies. It is thought that at later stages, urbanization not only acts as a restraint on carbon emissions [5,21,23] but may also become a driver for green development [25] if the tertiary industry develops alongside with the urbanization [33]. The studies included in this second category tend to view urbanization as a “necessary evil” needed to obtain a sustainable future in terms of environment. Moreover, it brings economic growth and can be adjusted so technological advancements (mostly smart or green tech) can help it on the way.

The third group of researches envelops the opinion that urbanization does not have a negative impact on the environment or, at least, the negative effects are explained not by actual urban regions but rather by the transition to urbanized areas and various factors connected with the process [36]. From this perspective, urbanization even tends to increase awareness of environmental impacts [37]. Moreover, it is considered that economic growth is the only way of ensuring environmental protection since growth is accompanied by new and less energy-intensive technological means of production. Urbanization is a catalyst for economic growth and as a result, urbanization promotes green development at the benefit of the environment [38].

Economic growth and urbanization are related to high energy consumption even in terms of industrialization or households’ consumption behavior. Previous studies show a positive correlation between economic growth and energy consumption [39–44]. More recent research shows no long-run relationship between the two [45] or even suggesting that renewable energy consumption has a more effective impact on the economic growth [46,47].

It was also discussed that the total and the nonrenewable energy consumption (residential or industrial) have a positive impact on carbon emissions [48]. As economic development remains a major objective for all world economies and is the only feasible means of accomplishing some of the sustainability goals (no poverty, zero hunger, decent work, and economic growth), the decision-makers are approaching two major directions for solving the energy issue; namely the usage of environmentally friendly energy sources (cutting from the total energy consumption the amount generated by the non-renewables), and the implementation of energy-saving technologies and industrial processes (including circular economy) [49].

The urbanization planners and decision-makers ought also to consider that households are responsible for the carbon emissions related to their final energy consumption but also for the production-related CO_2 incorporated in different goods and services [50]. It is critical, therefore, to develop multi-dimensional analysis to identify solutions that will improve environmental sustainability while maintaining the social and economic welfare and progress [51–53]. Considering that the environmental impact of urbanization remains a hot issue nowadays, fact revealed by the multitude of research in this topic [54,55] with radically different conclusions and some researchers recommend, as future research directions, the analysis of different coupling relationship between different parameters [56] in order to provide a more enlightenment related to the practice of healthy urbanization and the environment [32], the present study targets to investigate the relationship between urbanization, energy-related features and carbon emissions in a region less analyzed as a group by previous research, considering a time interval between 1990 and 2015, when most of the countries from our panel were just exiting from the communist era.

2. Materials and Methods

2.1. Dataset Description

The present study considers analysis data from the period between 1990 and 2015, related to ten South-East ex-communist European countries, as follows: Romania, Bulgaria, Hungary, Serbia, Poland, Slovenia, Slovakia, Albania, Czech Republic, and Bosnia. It must be considered regarding the literature analysis, previously shared in this study, that there is a vast number of research studies, presented above, regarding the Asian emerging economies, but less extensive literature related to European developing regions. Therefore, the importance of this study is revealed by the fact that the dataset was collected during a period of 26 years, just after the fall of communist regimes and during a transition period. The present paper reunites data from all the above-mentioned countries, to determine the relationship between urbanization and energy intensity on CO_2 emissions. The countries included in the research, all former communist economies, have emerging trends but different industrial composition [57]. Moreover, the countries' industrial reorganization and urbanization process claims a high level of energy consumption and the critical economic transformations relate to the energy intensity as recent studies have shown [58]. However, more recent data from the last 5 years could not be used in this study as not all the countries considered for dataset elaboration had reported data related to the analyzed parameters. The dataset used in this research was collected from three main sources and described within Table 1. Thus, the energy-related variables were selected from the EIA database (eia.gov), while the urbanization (urban population and urban population growth) and carbon emission data were collected from the "Our World in Data" (ourworldindata.org) and from the World Bank databases (data.worldbank.org). In order to describe the energy-related parameters, the energy consumption (coal, natural gas, electricity, and total) for different destinations (commercial, residential, industrial, and transportation) and energy production (crude oil, natural gas, and hydro) were introduced into the feature importance assessment. Both the effects of urbanization and energy intensity upon the environment, but also of the energy components were selected for the analysis, to offer a better description of how parts of urban-driven activities and energy-related elements affect CO_2 emissions. Thus, it is considered that while energy intensity describes the efficiency of energy usage, the analyzed components would elucidate the consumption structure and the importance of each element (by destination and source).

Table 1. Dataset parameters detail.

Variable (Unit Measure/Year)	Mean	Minimum	Maximum	Description
CO_2 Emissions (million tons)	80.54	1.53	377.41	The overall CO_2 emissions
Energy_Intensity (MJ/$2011 PPP GDP)	7.65	2.89	47.11	Energy Intensity
Urban_Population (persons)	6574,510.32	1004,706.00	23,842,562.00	Urban population number
Urban_Population_Growth (%)	0.06	−2.95	2.18	The rate of urban growth
En_Coal_Prod (ktoe)	12,527.08	1.00	98,969.00	Energy production obtained from coal
En_CrudeOil_Prod (ktoe)	1196.17	1.00	7697.00	Energy production obtained from crude oil
En_NaturalGas_Prod (ktoe)	2088.05	2.00	22,911.00	Energy production obtained from natural gas
En_Hydro_Prod (ktoe)	432.13	13.00	1737.00	Energy production obtained from hydro sources
En_Total_Prod (ktoe)	19,306.77	758.00	103,876.00	Total energy production
En_TotalCoal_Cons (ktoe)	2630.80	8.00	24,017.00	Total Energy Consumption based on coal
En_TotalCrudeOil_Cons (ktoe)	5.74	1.00	48.00	Total Energy Consumption based on crude oil
En_TotalNaturalGas_Cons (ktoe)	3773.02	1.00	19,854.00	Total Energy Consumption based on natural gas
En_TotalAll_Cons (ktoe)	17,541.18	841.00	69,977.00	Total Energy Consumption based on all sources
En_IndustryCoal_Cons (ktoe)	1308.93	6.00	12,496.00	Energy Consumption in industry based on coal
En_IndustryCrudeOil_Cons (ktoe)	5.70	1.00	48.00	Energy Consumption in industry based on crude oil
En_IndustryNaturalGas_Cons (ktoe)	1530.95	1.00	16,767.00	Energy Consumption in industry based on natural gas
En_IndustryAll_Cons (ktoe)	5304.41	102.00	24,298.00	Energy Consumption in industry based on all sources
En_TransCoal_Cons (ktoe)	13.79	1.00	173.00	Energy Consumption in transportation based on coal
En_TransNaturalGas_Cons (ktoe)	12,527.08	1.00	98,969.00	Energy Consumption in transportation based on natural gas
En_TransTotal_Cons (ktoe)	3241.10	135.00	17,154.00	Energy Consumption in transportation based on all sources
En_ResidCoal_Cons (ktoe)	1195.95	1.00	9859.00	Residential Energy Consumption based on coal
En_ResidNaturalGas_Cons (ktoe)	1350.74	1.00	3947.00	Residential Energy Consumption based on natural gas
En_ResidTotal_Cons (ktoe)	5074.58	354.00	24,410.00	Residential Energy Consumption—all sources
El_Total_Cons (MW/h)	32,600.32	1275.00	127,819.00	Total electricity consumption
El_Industry_Cons (MW/h)	13,408.10	361.00	49,482.00	Total electricity consumption in industry

Table 1. *Cont.*

Variable (Unit Measure/Year)	Mean	Minimum	Maximum	Description
El_Trans_Cons (MW/h)	1304.97	12.00	5481.00	Total electricity consumption in transportation
El_Resid_Cons (MW/h)	9511.39	529.00	28,615.00	Residential total electricity consumption
El_CommServ_Cons (MW/h)	7647.50	30.00	45,443.00	Commercial spaces total electricity consumption
En_Coal_CommCons (ktoe)	275.63	1.00	2276.00	Commercial spaces energy consumption based on coal
En_CommercialNaturalGas_Cons (ktoe)	692.73	2.00	2403.00	Commercial spaces energy consumption based on natural gas
En_CommercialAll_Cons (ktoe)	1765.18	3.00	8821.00	Commercial spaces energy consumption based on all sources

Previous studies proved that in the case of developing economies, such as those considered in our research, the economic growth is even exceeded by the carbon production [59] and their energy consumption is one of the main drivers for it.

2.2. Analysis Methodology

The present study consists of two stages of describing the urbanization and energy-related variables on carbon emissions. First, ensemble learning was used—a collection of machine learning algorithms—to examine the feature (variables) importance of the afore mentioned parameters.

Afterwards, fixed-effect panel data methodology was applied to describe the impact of urbanization and energy intensity upon carbon emissions.

Following the panel data analysis, the current research quantifies, by using a multiple linear regression approach, the most relevant linear relationships that explain the variance of the CO_2 emissions parameter.

The ensemble learning methods used for determining the feature importance among parameters related to CO_2 predictions can identify both linear and non-linear parameter relations, as such it could prove useful in identifying what linear models could be analyzed.

As emphasized by previous research [60], despite significant successes related to knowledge discovery, traditional machine learning can struggle when dealing with complex data like high-dimensional, imbalanced, or noisy data. This is because it could prove difficult for these methods to capture the underlying structure of the data.

Ensemble learning integrates data mining, data fusion, and data modeling, into a unified framework. These algorithms firstly extract a set of features with a variety of transformations, afterwards multiple learning algorithms are utilized to produce weak predictive results and, finally, the ensemble learning unifies the knowledge obtained from the above results achieving a better predictive performance.

Also, Sagi [61] shows that ensemble methods can improve the predictive performance of a single model by training multiple models and combining their predictions. There are multiple advantages to utilizing ensemble algorithms, as compared to other algorithms [62,63]: (a) easy to understand and visualize; (b) ensemble algorithms are non-parametric which means they are not requiring a particular data distribution; (c) mixed data types can be used, even if the categorical variables should be one hot encoded; (d) the prediction and accuracy performance of the model is not affected by the multi-collinearity of the features; (e) ensemble algorithms are not prone to overfitting; (f) the outliers and noise are well handled; (g) there is no need to scale the inputs; (h) when compared to neural networks or Support Vector Machines, they are computationally faster; (i) their performance is better than the one provided by the weak learners that are not similarly accurate because of the high variance.

Boosting and bagging algorithms provides the most accurate tree-based ensemble models [64]. Boosting is based on the embedding of many weak learners into one efficient regression/classification algorithm, while "bagging" involves a non-sequential learning that draws, with replacement, a random subset of data from the training dataset. These draws are not correlated in any way, but displays the same distribution. The selected data is used to implement a weak learner (decision tree). The most popular class (or average prediction value in case of regression problems) is then chosen as the final prediction value [65,66].

The AdaBoost algorithm is part of the boosting algorithms family and it was introduced in [63]. The decision trees (weak learners) are grown sequentially as weak learners that are able to penalize incorrectly predicted samples by assigning at each prediction round larger weights to the incorrect predicted samples. Thus, the algorithm is able to learn from previous mistakes. For a regression problem, the accepted prediction comes from a weighted median.

There are some characteristics specific to the AdaBoost algorithm. As an example, the AdaBoost algorithm can avoid overfitting even in low noise datasets [67]. Also, the number of hyper parameters that must be tuned to improve model performance is not very high (the learning rate, the number of iterations/rounds, the maximum depth of the weak learners/decision trees). Still, for data with a lot of noise, the AdaBoost performance can vary. Freund [64] emphasizes that it generalizes well, while Oza [68] states that noisy data usually leads to performance issues because the algorithm spends a lot of time on learning extreme cases, while skewing the results.

The random forests algorithm uses the bagging approach. Thus, it randomly chooses subsamples for each iteration of growing trees, bootstrapping the data. The reduction of the overfitting is managed by the random forest algorithm by combining several weak learners that under fit as they are utilizing only a subset of all input samples. Hence, the random forests differ from AdaBoost as AdaBoost chooses only a random subset of features to be included in each tree, while the random forest includes all features for all trees.

Due to its accuracy, robustness against noise and outliers, speed, and feature selection possibility random forest is a popular algorithm [62,69–72]. Another advantage of random forests when compared to AdaBoost is the fact that it is not so affected by noise, generalizing better a reduced variance as the generalization error displays a limit with an increasing number of trees being grown [60]. However, in the case of random forest, the number of hyper parameter that needs tuning is high (maximum depth of trees, number of trees, number of features, whether to bootstrap samples, the minimum number of samples left in a node before a split and the minimum number of samples left in the final leaf node) [73,74]. Too much complexity in the training phase could lead to overfitting, thus a lower number of features should be chosen (around one third). Additionally, a larger number of trees usually leads to a better performance, while the maximum depth as well as the minimum number of samples per leaf before splitting should be relatively low.

XGBoost algorithm, presented in [75] is based on the gradient tree boosting concept used to reduce overfitting through regularization parameters. Gradient boosted trees use regression trees in a sequential learning process as weak learners. The regression trees are similar to decision trees, except that they are using a continuous score assigned to each leaf, that will be summed up for getting the last prediction. For every iteration i which grows a tree t, scores w are calculated which predict a certain outcome y [76]. The overall score is minimized through the learning process involving the loss function at i-1 and the new tree structure of t.

Gradient descent is then used to compute the optimal values for each leaf and the overall score of tree t. The score is also called the impurity of the predictions of a tree.

XGBoost is characterized by high computational speed and by the regularization parameter that successfully reduces variance. XGBoost is more difficult to tune compared to AdaBoost and random forests, as it is described by a multitude of hyper parameters (learning rate, column subsampling and regularization rate, subsample, maximum depth of trees, minimum weights in child notes for splitting and number of estimators (trees)) [77].

The overfitting decrease is obtained through regularization and weights in child notes, respectively higher values for the number of estimators, keeping the maximum depth, learning rate and column subsampling at lower values to achieve reduced overfitting [78]. The feature importance metric, provided by the above models, measures how often and how much a feature was used in the model (in most cases, to make a split in a tree).

If a feature is removed, the model may make up for its absence by finding other remaining features that hold some of the same distinguishing information, i.e., features that are correlated with the removed feature. Thus, the feature importance describes which features are relevant, providing a better understanding of the problem. The previous ensemble methods use 3 ways of computing the feature importance: (a) Gini importance (or mean decrease impurity) measures how each feature decreases the impurity of the split (the feature with highest decrease is selected for internal node) [79]; (b) mean decrease accuracy computes the feature's importance on permuted out-of-bag (OOB) samples based on mean decrease in the accuracy [80]; (c) the permutation based importance randomly shuffle each feature and compute the change in the model's performance [81]. The features impacting performance the most are the most important ones.

The multiple linear regression method (MLR) was used in the current research for identifying and testing multiple linear regression models, having CO_2 as the dependent variable and various independent variables determined by using feature selection techniques (ensemble methods feature importance) further combined with stepwise selection technique having as the inclusion criteria, the statistical significance at $p < 0.05$ and the Variance Inflation Factor (VIF) index less than 10 in order to avoid the multi-collinearity effect.

The MLR are excellent for quantifying the existing linear relationships between one dependent variable and several independent variables. The MLR models offer the possibility of quantifying the relationship between variables, being easy to implement and efficient to train the data.

Overfitting is avoided by using dimensionality reduction and cross-validation. The optimal features were selected so the machine learning models perform better. When the number of features is high, selecting the optimal features is important, as it is not necessary to use each available feature in implementing the algorithms. Thus, the algorithm was only fed with important features that can explain the dependent variable. It should be mentioned that all the linear models presented in this research were validated against the following assumptions: **(a)** there are no multi-collinear features, hence the predictors are not highly correlated. As such, only parameters with a low (below 10) Variance Inflation Factor (VIF) were considered; **(b)** there is a linear relationship between predictors and the outcome. The non-linearity of the model was determined by using the residual plot of fitted values versus the residuals. Presence of a pattern in the residual plot would imply a problem with the linear assumption of the model; **(c)** the homoscedasticity is another assumption of a linear regression model. The error terms may, for instance, change with the value of the response variable in case of non-constant variance (heteroscedasticity) of errors; **(d)** The consecutive error terms are uncorrelated (Durbin–Watson test). Also, all presented MLR algorithms were trained on 60% of the data (100 samples) and tested on the remaining 40% (66 samples).

3. Results and Discussion

The high number of samples available in our dataset allowed the application of three machine learning algorithms (presented in the above section) to determine the most important features for predicting the CO_2 emissions value. The weights associated with each feature quantifies its importance in predicting the dependent variable (CO_2 emissions)—see Table 1.

The parameters with the highest weight value are the ones most influential in the prediction model. The machine learning ensemble methods can identify both linear and non-linear relations between the predictors and the dependent variable, so the feature importance analysis could be a first step in identifying potential linear models that could be further investigated.

The results provided by the three models involved in the feature importance analysis displayed good consistency, the most important features being similar among the models. In Table 2, the highlighted items are not only the first ten items according to their importance, but the highlighting also shows that the first ten features were all identified as being important for the prediction model by more than one model.

Table 2. Feature Importance (Weight Values)—Various Ensemble Methods.

RANDOM FOREST (RMSE: 9.80)	ADA BOOST (RMSE: 4.54)	XGBOOST (RMSE:5.20)
En_CommercialAll_Cons (0.24)	**El_CommServ_Cons (0.36)**	**En_IndustryAll_Cons (27)**
En_TransTotal_Cons (0.15)	**En_ResidCoal_Cons (0.12)**	**El_Industry_Cons (27)**
El_Resid_Cons (0.12)	**Urban_Population (0.11)**	**En_ResidCoal_Cons (25)**
El_CommServ_Cons (0.10)	**El_Trans_Cons (0.10)**	**En_TransNaturalGas_Cons (25)**
En_ResidCoal_Cons (0.10)	**En_TransNaturalGas_Cons**	**En_IndustryCoal_Cons (23)**
El_Trans_Cons (0.07)	**En_CommercialAll_Cons (0.05)**	**En_IndustryNaturalGas_Cons (22)**
Urban_Population (0.07)	**En_TransTotal_Cons (0.04)**	**Urban_Population (22)**
En_TransNaturalGas_Cons	**En_ResidTotal_Cons (0.04)**	**El_Trans_Cons (22)**
En_ResidTotal_Cons (0.05)	**El_Resid_Cons (0.04)**	**Urban_Population_Growth (21)**
El_Industry_Cons (0.02)	**En_IndustryAll_Cons (0.02)**	**Energy_Intensity (20)**
En_IndustryAll_Cons (0.02)	Energy_Intensity (0.01)	El_Resid_Cons (18)
En_IndustryCoal_Cons (0.01)	El_Industry_Cons (0.01)	En_CrudeOil_Prod (18)
Energy_Intensity (0.01)	En_IndustryNaturalGas_Cons (0.01)	En_TransTotal_Cons (17)
En_IndustryNaturalGas_Cons (0.00)	En_IndustryCoal_Cons (0.01)	En_ResidTotal_Cons (16)
En_Coal_CommCons (0.00)	En_ResidNaturalGas_Cons (0.00)	En_Hydro_Prod (11)
En_CrudeOil_Prod (0.00)	Urban_Population_Growth (0.00)	En_Coal_CommCons (10)
En_NaturalGas_Prod (0.00)	En_CrudeOil_Prod (0.00)	El_CommServ_Cons (9)
Urban_Population_Growth (0.00)	En_Coal_CommCons (0.00)	En_CommercialAll_Cons (6)
En_CommercialNaturalGas_Cons (0.00)	En_CommercialNaturalGas_Cons (0.00)	En_CommercialNaturalGas_Cons (5)
En_Hydro_Prod (0.00)	En_NaturalGas_Prod (0.00)	En_NaturalGas_Prod (5)
En_ResidNaturalGas_Cons (0.00)	En_Hydro_Prod (0.00)	En_ResidNaturalGas_Cons (5)

Furthermore, the XGBoost algorithm used in its prediction model several variables identified as important that were not captured by Random Forest or ADA Boost algorithms, variables that further proved useful in determining relevant linear regression models, having CO_2 Emissions as variable of interest. Secondly, after analyzing the features' importance in CO_2 emissions prediction models, to get the first perspective over CO_2 emissions influencers, an exploratory data analysis (EDA) was performed.

The EDA charts graphically depict the existing relations between CO_2 emissions and various indicators. Thus, the presented charts emphasize the following: total energy production and CO_2 emissions/country clustering, urban growth rate and CO_2 emissions/country clustering, sectorial Energy Consumption vs. CO_2 emissions/year and CO_2 emissions, and various types of energy production/all countries.

Figures 1 and A1 (left cut of Figure 1, having Poland excluded), describe the way energy production affects carbon emission level among the countries comprised by our study. It is obvious that Poland, with the largest amount of produced energy, emits the largest amount of CO_2, which also confirms the overall strong positive linear relationship between the energy-related features and pollution, as production is based on nonrenewable sources. However, Slovakia, Bulgaria, and Hungary registered a higher level of CO_2 emissions in relation to total energy production, compared to the rest of the analyzed countries (Figure 1).

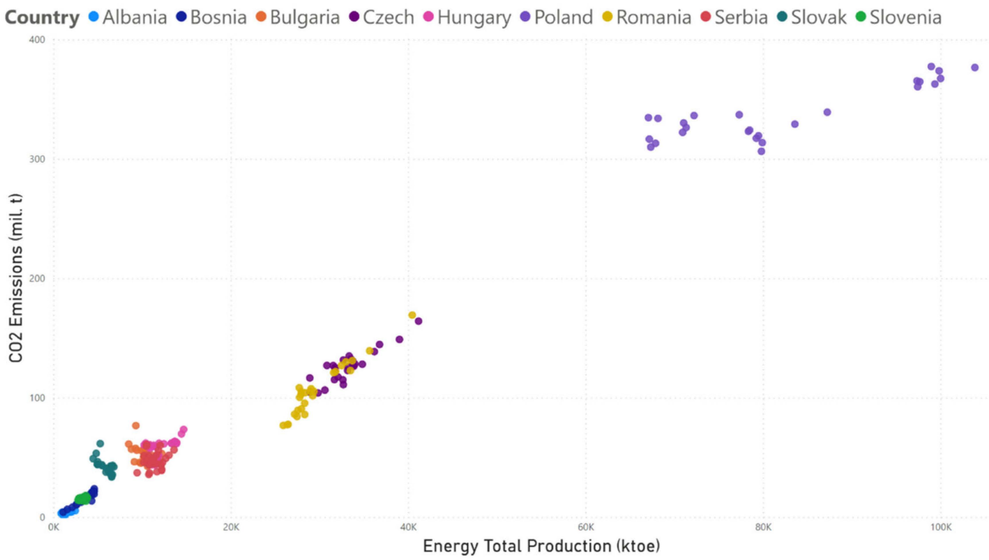

Figure 1. Energy Total Production and CO_2 emissions—Country Clusters (1990–2015).

Also, as depicted in Figure 2, for most countries, the urban growth rate is not necessarily related with the CO_2 emissions value.

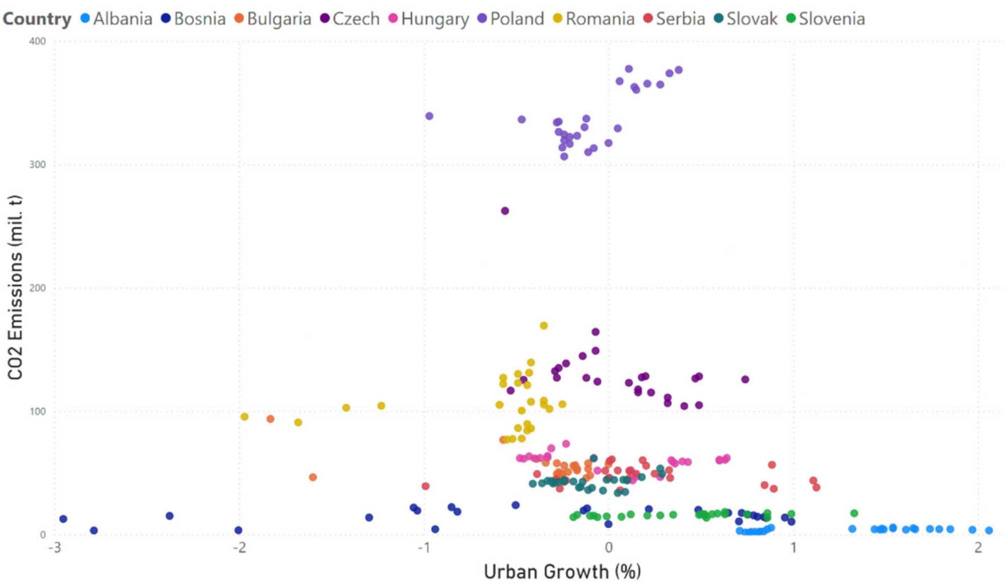

Figure 2. Urban growth and CO_2 emissions—Country Clusters (1990–2015).

For most of the country clusters, the data points show steady values regardless of the value of the urban growth, with two exceptions: (a) Poland, that clearly displays a linear increase of the CO_2 emissions when the urban growth rate is increasing; (b) Czech Republic that shows a descending trend of the emissions, while the urban growth rate is increasing.

The correlation between carbon emissions and sectorial energy-related features is explained in Figure 3.

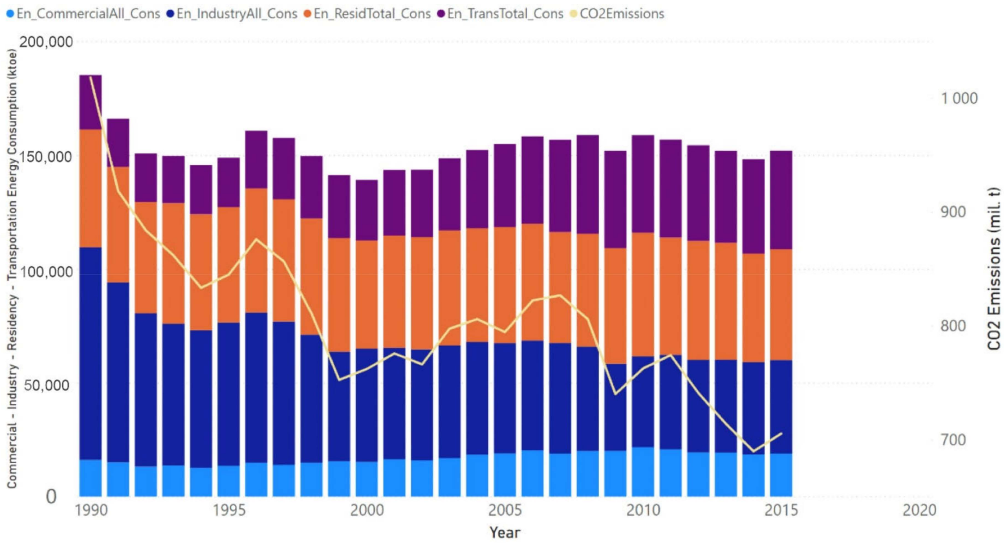

Figure 3. Sectorial Energy Consumption vs. CO_2 emissions time series.

As it can be observed (Figure 3), the structure of the energy consumption is changing along the analyzed time interval, as the industrial consumption is declining in a fashion determined by the structural economic developments. Thus, the carbon emission curve evolves mostly in connection with the industrial energy consumption, while the total energy consumption is not displaying a clear ascending or descending trend.

However, the chart also emphasizes that the energy consumption in the transportation industry steadily increased during the past 15 years, similar the energy consumption for the commercial buildings.

Figure 4 presents a country level dashboard describing the CO_2 emissions together with the different types of energy production.

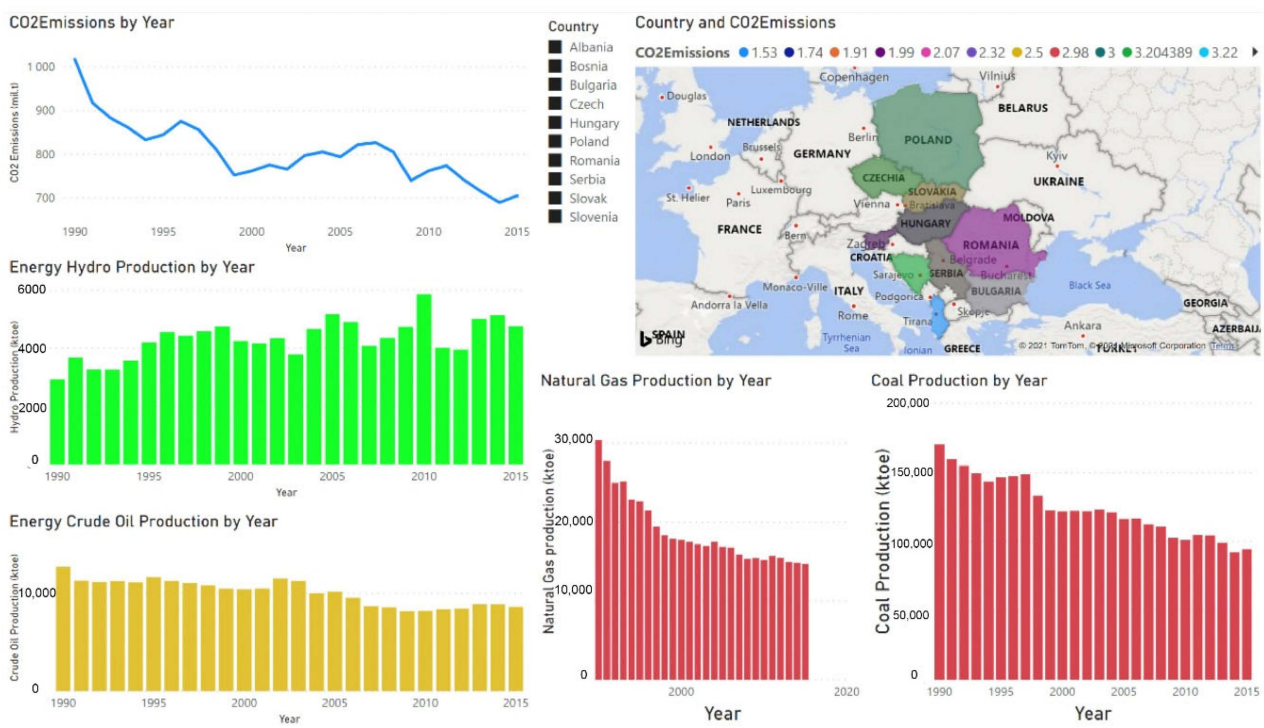

Figure 4. CO_2 emissions and type of energy for the country set (1990–2015).

The above dashboard allows country level analysis of the emissions and energy production, still the overall situations clearly displayed that the emissions downward trend is mainly associated with the overall decrease of the natural gas and coal energy production. Thus, according to Figure 4, the decrease of non-renewable energy consumption leads to a decrease in CO_2 emissions.

The fact proves a modernization of the economies in the region due to their structural reforms during the 1990s and early 2000s. It is also proof of a new path in energy production based on renewable sources, but also of a reinterpretation of the industrial structure and localization.

Following the exploratory data analysis stage, this research uses both a data panel analysis and a multiple linear regression approach for formalizing the existing relation between CO_2 and urbanization, a relationship clearly identified through the EDA (Exploratory Data Analysis) visualizations and feature importance machine learning algorithms.

The fixed-effect panel data model uses as parameters the carbon dioxide emissions, energy intensity, population growth, and urban population collected over a period of 26 years (1990–2015) for the ten countries in the Central—Southeastern Europe.

The reasons for choosing only these parameters from a larger dataset (Table 1) are as follows: (a) this research aimed to identify a model that would clearly describe urbanization—CO_2 emissions; (b) the data panel analysis requires a complete data set—data available for all years, all countries, and all parameters.

The regression model is as follows:

$$CO\_2_{it} = c + a_1 energy_{it} + a_2 ug_{it} + a_3 up_{it} + u_{it} \tag{1}$$

where:

- CO_2_{it}—CO_2 emissions;
- $energy_{it}$—energy intensity;
- ug_{it}—urban population growth;
- up_{it}—urban population;
- u_{it}—represents the error, which is composed of three parts: individual-specific unnoticed effect (α_i), time-specific unnoticed effect (μ) and individual and time-specific unnoticed effect (ε_{it});
- c—represents the constant or the intercept;
- a_1, a_2, a_3—model parameters to be estimated (their values are other than 0).

Given that the time dimension is larger than the cross-sectional dimension, we proceed with the verification of the stationarity for each variable. If only some variables are non-stationary, the use of these values in the model analysis will generate an unreliable and unrealistic model. According to both the data presented in Table 3 and the six tests, none of the four series is stationary.

To be able to go further, first-order differences were realized, which also led to the series being stationary. After verifying the stationarity, the Johansen co-integration test was applied in order to verify whether there is a statistically significant long-term connection between the variables. If such a co-integration exists, it shows us that the combination of variables is stationary, and it will be possible to continue estimating the model using non-stationary variables.

Analyzing the values of Johansen Co-integration (Table 4) and using statistical hypotheses (H0 null hypothesis—there is no co-integration and H1 alternative hypothesis—there is co-integration) the results show that the series is co-integrated, which presupposes that all variables together are stationary in the long term. After verifying the co-integration, the assessment continues with the model estimation using one of the three methods: Pooled Ordinary Least Square method (POLS), Fixed Effect (FE) method, and Random Effect (RE) method. To determine the relevant model, a series of statistical tests will be performed. To choose between the FE model and the RE model, the Hausman statistical test will be used to test the lack of correlation between unobserved effects and regression variables.

The Breusch–Pagan test will be used to choose between the FE and POLS models to test for the presence of an unnoticed effect. The F test for the FE model will also be used to test whether all unobservable effects are zero, thus distinguishing between POLS and FE. Using a regular regression and the POLS method, no distinction will be made between countries, thus denying the heterogeneity or individuality of each country. If a panel regression was used, it can be concluded that the individuality of each country was considered [82]. The results obtained for the regression equation using the methodologies for Pooled OLS, FE, and RE are presented in Table 5. According to the Breusch–Pagan, F tests for fixed-effect models, and the Hausman test, the best method for estimating the model is the fixed-effect panel data method.

Table 3. Panel unit root tests.

Test Statistic	CO_2 Emissions	Energy Intensity	Urban Population	Urban Population Growth
		Levin, Lin, Chu		
Level	−2.41 (0.00)	−2.22 (0.01)	−0.97 (0.16)	−0.49 (0.30)
		Im, Pesaran, Shin W-test		
Level	−1.86 (0.03)	−0.06 (0.47)	1.31 (0.90)	−3.25 (0.00)
		ADF-Fisher Chi-square		
Level	33.87 (0.02)	30.09 (0.06)	28.16 (0.10)	45.46 (0.00)
		PP-Fisher Chi-square		
Level	48.75 (0.00)	29.48 (0.07)	17.37 (0.62)	33.49 (0.02)
		Breitung		
Level	−0.13 (0.44)	−1.40 (0.07)	0.66 (0.74)	0.17 (0.56)
		Hadri		
Level	9.26 (0.00)	6.42 (0.00)	11.60 (0.00)	2.80 (0.00)

Table 4. Johansen Co-integration.

Hypothesized No. of CE(s)	Fisher Stat.* (From Trace Test)	Probability (Prob.)	Fisher Stat.* (From Max-Eigen Test)	Prob.
None	192.7	0.00	117.3	0.00
At most 1	101.2	0.00	77.37	0.00
At most 2	45.78	0.00	39.76	0.00
At most 3	33.72	0.02	33.72	0.02

* Probabilities are computed using asymptotic Chi-square distribution.

After establishing the type of model, the correlation of the residues with the Pesara CD test was checked. The series of the random variable does not show the correlation phenomenon. Regarding homoscedasticity, after applying the modified Ward test, the model is heteroscedastic and chosen to correct this hypothesis using Cross-section SUR (Cross-section Seemingly Unrelated Regressions). The results obtained by applying SUR method are presented in Table 6.

Table 5. Estimation of parameters for the model.

Exogen Variables	**POLS**	**FE**	**RE**
energy_intensity	1.52 (0.00)	0.49 (0.00)	0.67 (0.00)
urban_population	1.46×10^{-5} (0.00)	2.64×10^{-5} (0.00)	1.61×10^{-5} (0.03)
urban_population_growth	10.61 (0.00)	2.29 (0.05)	3.30 (0.00)
Constant	−27.92 (0.00)	−96.63 (0.00)	30.55 (0.00)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	260	260	260
R^2	0.94	0.99	0.53
AIC	9.00	7.36	
Breusch–Pagan test(POLS versus RE)			1844.38 (0.00)
F-test for fixed effects(POLS versus FE)			124.12 (0.00)
Hausman test(FE versus RE)			116.70 (0.00)

Table 6. Fixed Effect model using the Cross-Section SUR method.

Dependent Variable: CO_2				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	−98.83	3.97	−24.85	0.00
ENERGY_INTENSITY	0.46	0.01	23.98	0.00
URBAN_POPULATION_GROWTH	1.82	0.17	10.19	0.00
URBAN_POPULATION	2.67×10^{-5}	6.12×10^{-7}	43.63	0.00
Effects Specification				
Cross-section fixed (dummy variables)				
Weighted Statistics				
R-squared	0.99	Mean dependent var		5.36
Adjusted R-squared	0.99	S.D. dependent var		21.85
S.E. of regression	1.01	Sum squared resid		252.40
F-statistic	8184.49	Durbin-Watson stat		1.28
Prob. (F-statistic)	0.00			
Unweighted Statistics				
R-squared	0.99	Mean dependent var		80.54
Sum squared resid	21,699.33	Durbin–Watson stat		0.34

Analyzing the data provided by the new model, it can be observed that an increase by one unit of energy intensity will increase carbon dioxide by 0.469030 units. The increase in carbon dioxide will be 1.82 units as population growth is increased by one percentage. As far as the total urban population is concerned, this will increase carbon dioxide in the atmosphere, but to a much lesser extent.

The trends presented in Figures 5 and 6 confirm that our study determines and visually describes the relationship between urbanization, carbon emissions, and energy consumption.

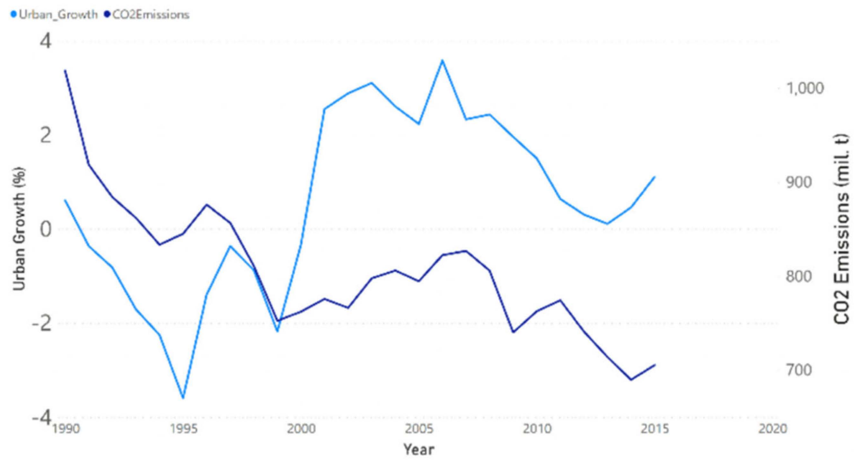

Figure 5. Urban population growth and CO_2 emissions.

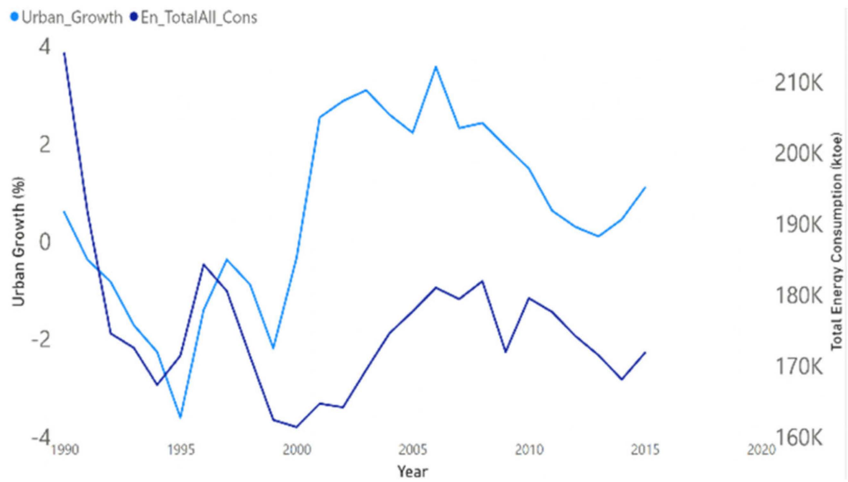

Figure 6. Urban population growth and energy consumption.

The panel data analysis properly formalized the strong existing relation between CO_2 emissions and energy intensity, urban population growth, and total urban population. However, through a multiple linear regression approach, the available data allowed an even deeper analysis of the CO_2 emissions, taking into consideration energy-related parameters associated with the urbanization process. As such, a number of eight relevant MLR models were identified, each of them described by high values of the adjusted R-Sq both on training and test data—see Table 7.

The in-depth analysis based on the MLR linear regression models gives us a detailed image on how carbon emissions evolve depending on energy-related variables and urbanization. The first two models (Equations (2) and (3)) explain the influence of electricity consumption (2) and total energy consumption on CO_2 emissions (3). Thus, according to Equation (2), there is a strong positive impact of all parameters on CO_2 emissions: a 1% increase in electricity consumption in transportation or households or industry will lead to 0.27%, 0.42%, and 0.61% increase of the CO_2 emissions, respectively. Based on the equation coefficients, electricity consumption belonging to industry affects CO_2 emissions the most, followed by the households' electricity consumption. Thus, for the 10 countries in our study, industrial electricity consumption holds an important share in explaining CO_2 emissions variance.

Table 7. Linear equations adjusted R-Sq and test R-Sq.

Equation No.	Adjusted R-Sq	Test Data R-Sq
(2)	95.60%	94.40%
(3)	96.00%	94.00%
(4)	91.60%	91.20%
(5)	95.52%	93.57%
(6)	75.68%	65.41%
(7)	78.14%	73.96%
(8)	87.78%	87.17%
(9)	87.78%	87.17%

The model presented in Equation (3), related to energy consumption, displays the same important share for industrial consumption and confirms the importance of the sector in terms of carbon emissions. Accordingly, a 1% increase of the energy consumption per industry, transportation or households leads to 0.6%, 0.18%, respectively, to a 0.31% increase of the CO_2 emissions.

$$CO_2Emissions = -3.22 + 0.27 * \text{El\_Trans\_Cons} + 0.42 * \text{El\_Resid\_Cons} + 0.61 * \text{El\_Industry\_Cons} \quad (2)$$

$$CO_2Emissions = -2.17 + 0.60 * \text{En\_IndustryAll\_Cons} + 0.18 * \text{En\_TransTotal\_Cons} + 0.31 * \text{En\_ResidTotal\_Cons} \quad (3)$$

The urban population linearly explains the CO_2 emission values (Equations (4) and (5)), a 1% increase of the urban population leading to a 1% increase of the CO_2 emissions. These results also confirm the findings reported by other authors [83–85] that the urban population scale is an important factor in residential energy consumption and CO_2 emissions.

Also, as observed in Equation (4), the energy intensity also influences the CO_2 emissions, a 1% increase of the energy intensity leading to a 0.49% increase of the CO_2 emissions.

$$CO_2Emissions = -5.48 + 0.47 * \text{Energy\_Intensity} + 1.02 * \text{Urban\_Population} \quad (4)$$

$$CO_2Emissions = -5.00 + 1.01 * \text{Urban\_Population} \quad (5)$$

As backed by other authors [86], this research study shows that the households also have an impact on carbon emissions in terms of energy consumption based on coal and natural gas (model 6), the contribution of the two energy-related variables being not significantly different, a one percent increase of each variable, if the other one remains constant, leading to a 0.30% and 0.22% increase of the CO_2 emissions, respectively.

$$CO_2Emissions = 0.46 + 0.30 * \text{En\_ResidCoal\_Cons} + 0.22 * \text{En\_ResidNaturalGas\_Cons} \quad (6)$$

The last three models (Equations (7)–(9)) discuss individual relationships between energy-related features (residential and transportation energy consumption), urbanization and carbon emissions. As presented in Table 7, all three models show high values for the adjusted R-sq, explaining how the transportation and households' energy consumption (two major features for urban areas and urban development) are influenced by the urban population and also how they determine the CO_2 emissions.

$$\textbf{En\_TransTotal}_{\textbf{Cons}} = -2.22 + 0.84 * \text{Urban\_Population} \quad (7)$$

$$\textbf{En\_ResidTotal\_Cons} = -3.30 + 1.02 * \text{Urban\_Population} \quad (8)$$

$$CO_2Emissions = -1.57 + 0.93 * \text{En\_ResidTotal\_Cons} \quad (9)$$

As it can be observed in the above equations, the urban population displays a consistent impact on energy consumption levels both for transportation and households, a 1% increase of the urban population leading to a 0.84% increase in the transportation energy consumption, respectively, 1.02% of the household's energy consumption. Due to the high correlation (0.87) existing between the transportation energy consumption and residential energy consumption, the CO_2 emissions variance is explained by using the parameter semantically closer to the urbanization process, that is residential energy consumption. Thus, it was possible to identify that an overall household's energy consumption increase of 1% will lead to a 0.93% increase in CO_2 emissions, confirming what was emphasized by other authors [87], that is, that the direct energy consumption of urban households heavily influences the CO_2 emissions.

4. Discussion and Conclusions

The analysis of scientific literature emphasizes that most of the recent research was conducted in China or other Asian countries. The reason for this is explained by the authors as being attributable to the fact that these regions are still in full process of urbanization or have important asymmetries between the different regions of the same country (the case of China). It is considered that developed countries are already urbanized and have a clear image of the process's impacts. It is needed, therefore, to assess the urbanizing impact on environment especially during the urbanizing process. Even so, it is highly important to overview other study cases for emerging countries outside Asia because urbanization has an important component in the cultural dimension. Another fact is that a lot of emerging economies are in fact urbanized European countries from the ex-communist Eastern Block. These countries have an important rate of urban population, but the urban areas are still changing due to the structural transformations of the national economy.

Urbanization is considered a developing phenomenon, having stages and levels of complexity and being interrelated with a lot of other processes like population migration, economic growth, industrial diversification, infrastructure transformations, and so on. When it develops, urbanization determines changes in the geographic distribution of economic activities but also an increasing transportation diversification and intensity. It is also strongly connected to energy intensity and technological development, but not always as a determinant of the two but mostly in a mutual relationship. The complexity of urbanization is given by the complexity of modern human society and that social development supposes in the modern technological society. The variety of variables is similar to other modern phenomena, a sum of modernization factors from different dimensions (economic, social, demographic, technological, cultural, etc.).

According to other authors [88,89], long-run relationships could be distinguished between environmental degradation indicators, CO_2, economic growth, fossil fuels, natural resources, and renewable energy, while CO_2 is considered a temporary impact indicator. Therefore, this supports the methodology applied in present research, which analysis database distributed over a long period (26 years), predicting therefore the CO_2 emissions based on historical movements.

During the first stages, urbanization has a direct and positive impact on carbon emissions (most used descriptor for the environmental impact). Then, as urbanization continues, during its later stages of development carbon emissions levels stall and tend to decrease. The explanation for this is that the effort of transforming non-urban to urban areas is higher at the beginning and decreases afterwards by the time the main infrastructure is built and the population growth is less explosive. Moreover, when all urban facilities are in place, the economic growth reaches certain levels and the communities seek new approaches regarding its evolution, embracing sustainable development patterns and seeking to implement green technologies. There are previous studies which reported cointegration relations, identified among lower-middle income economies, which involves both CO_2 emissions and renewable energy. However, some authors [90–92] conducted research for determining the relationship between economic growth and environmental degradation measured by CO_2 emissions and revealed that only some countries were found to abide to the hypothesis according to which their income per capita once it reaches and increases beyond the kink point, it will generate afterwards, declining of CO_2 emissions. Also, other authors [93] reported positive effects of the per capita income and per capita CO_2 emissions on the renewable energy demand, a fact which confirms the strong bound between the economic and environmental sustainability. However, when an economy starts its increasing trend, an increase in its energy requirements, a decrease of the share of renewable sources, and an increase in environmental pollution from fossil sources will be registered, according to other authors [91]. The economic growth can be used as a tool in order to ameliorate environmental damage by providing eco-friendly machines and services [94].

The European Union (EU) member states' commitment regarding carbon reduction and cleaner environment by increasing the share of renewable energy in the energy portfolio [89] can be achieved through the mechanism of economic globalization [93]. Thus, the EU has a target of at least an average of 27% renewable energy by 2030, with France targeting 40%, Spain and Germany exceeding 30%, and Italy registering 16% in 2015. The use of panel data technique on European countries [95], considering a 14 years period dataset, revealed that the increase of gross domestic product (GDP) is the main factor which positively influences the renewable energy [92,95].

However, according to other authors [96], it is considered that if achieving a high level of energy efficiency, the concerns about emissions will be significantly diminished and insignificant relationship between economic growth and CO_2 emissions will appear.

The subject is still critical for most economies and regions as the societal urban organization is seen as a key factor for growth and for sustainability issues. Most of the researchers consider that an urban society is able to target sustainable development and to have a more environmentally friendly behavior. The desideratum is to reach to the stages of urbanization at which the society is more sustainability oriented. That is because during the first stages, the process supposes a high energy consumption and hence an important environmental impact (carbon emissions and others). Most of the authors identify the role of the decision-makers in finding the proper development patterns that ensure the minimum environmental impact on early stages and a fast orientation to green approaches later. Other authors [40] consider that stock market development is the key source of financing clean and renewable energy investment, allocating climate funds and sharing technological innovations—a positive energy consumption shock tends to increase countries′ environmental performance levels (EPI) while decreasing the level of CO_2 emissions. Also, other studies [88] consider that policies elaborated in order to improve environmental sustainability must be extended also to built-up land, carbon absorption land, crop land, fishing grounds or forest areas. Also, the natural resource abundance and green internet are considered to reduces per capita CO_2 emissions [91,96].

The value of the present study for the state of the art derives both from the methodology applied and the dataset used, as it employs machine learning algorithms for assessing the selected parameters attributed to a group of European emerging economies. Moreover, our empirical results confirm the relationship between urbanization and carbon emissions for the countries included in our study and between the different energy parameters and the CO_2 emissions as well.

It can be concluded that considering the present study's applied methodology, CO_2 is mostly influenced by industry energy consumption, followed by residential (coal and natural gas consumption), and the transportation sector's energy consumption. However, the urban population is directly related to both residential and transportation sector energy consumption. This could be due to a mode intense development of industrial sector outside the urban areas. Therefore, it can be considered that both energy consumption of residential and transportation sector can be considered proper indicators for the evaluation of urbanization impact on CO_2 emissions, for Central–Eastern European Countries.

Like most studies, the design of the current study is subject to limitations. The dataset does not include data from the previous five years since most of the analyzed countries did not revealed them. However, since CO_2 is considered a temporary impact indicator [88,89], as previously mentioned, the 26 year dataset time period could be considered substantial for emphasizing the impact of urbanization and other energy-related factors upon CO_2 emissions, for the studied area.

Thus, the present study includes a combination of methodological instruments meant to better describe the relationship between the chosen features. Also, the group of analyzed countries is not found in previous studies, nevertheless they have similarities with other developing regions around the globe.

The identified models confirm previous studies' observations made for other countries and regions. As a result, it may be concluded that the urbanization, as a process, affects the environment (carbon emissions) more than the actual urban regions do, as the urban growth has a larger effect in the identified model, on CO_2 emissions, compared to the total urban population. It is proper to say that urban areas tend to embrace modern, more green technologies; but the road to achieve urban and responsible areas is accompanied by not so environmentally friendly industries (such as cement industry) and a high consumption of nonrenewable energy.

After sampling the best fitted features using the machine learning algorithms, we developed explanatory linear regression models. These models aid in having an in-depth image on how carbon emissions evolve depending on energy-related variables and urbanization. Our findings relate with previous studies and confirm the fact that urbanization has an impact on carbon emissions. For the group of countries comprised in our study, the identified energy-related variables are also important for the carbon emission trends and should be considered by decision makers when planning green development strategies. Clearly, the non-renewable sources of energy influence CO_2, but also relate to the urbanization processes.

Author Contributions: Conceptualization, F.M.N. and A.C.N.; methodology, F.M.N., A.C.N., C.G.Z., S.-M.P., D.M. and D.S.C.; software F.M.N., A.C.N., C.G.Z., S.-M.P., D.M. and D.S.C.; validation, F.M.N., A.C.N., C.G.Z., S.-M.P., D.M. and D.S.C.; formal analysis, F.M.N., A.C.N., C.G.Z., S.-M.P., D.M. and D.S.C.; investigation, F.M.N., A.C.N., C.G.Z., S.-M.P., D.M. and D.S.C.; resources, F.M.N., A.C.N., C.G.Z., S.-M.P., D.M. and D.S.C.; data curation, F.M.N., A.C.N., C.G.Z., S.-M.P., D.M. and D.S.C.; writing—original draft preparation, F.M.N., A.C.N., C.G.Z., S.-M.P., D.M. and D.S.C.; writing—review and editing, F.M.N., A.C.N., C.G.Z., S.-M.P., D.M. and D.S.C.; visualization, F.M.N., A.C.N., C.G.Z., S.-M.P., D.M. and D.S.C.; supervision, F.M.N.; project administration, F.M.N. and D.S.C.; funding acquisition, F.M.N., A.C.N., C.G.Z., S.-M.P., D.M. and D.S.C. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

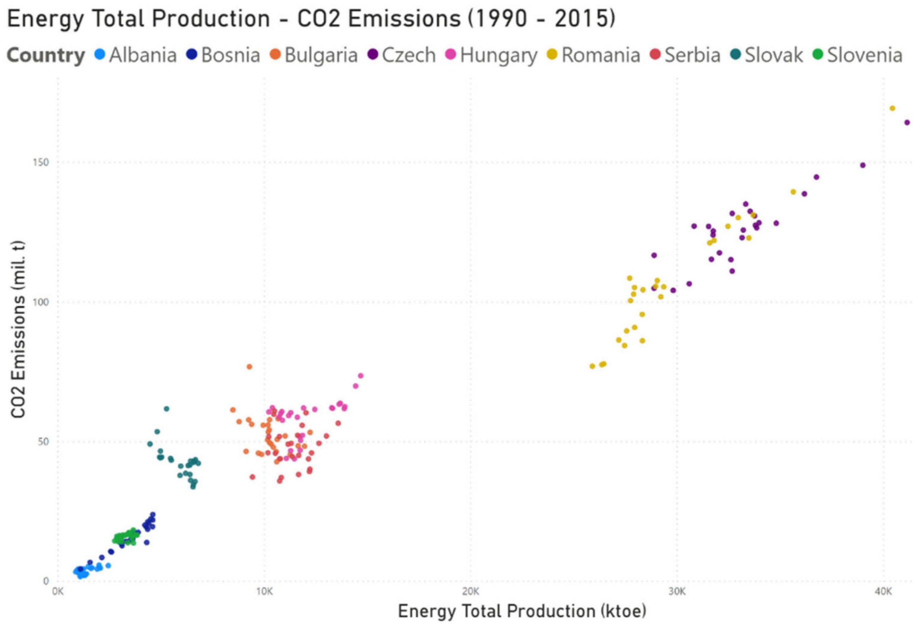

Figure A1. Energy Total Production and CO_2 emissions—Country Clusters (Poland excluded).

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